Modeling the Adoption Decision Process of Future Scanning and Optimizing Technology in Hardwood Sawmills

by

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(ABSTRACT)

A nation-wide survey of hardwood sawmills was conducted in the fall of 1999. The objectives of the survey were to determine the differences between adopters and non-adopters of scanning and optimizing technology, identify the company expectations of scanning and optimizing technology, and model the adoption decision process for future scanning and optimizing technology. These objectives were chosen because timely information was not available on the hardwood sawmill industry, and even less was known about the overall state of technology with the industry. The survey consisted of a mail questionnaire which was sent to over 2000 hardwood sawmills. The questionnaire was used to collect demographic, equipment, and preference scale information on the hardwood sawmill industry. The second part of this project used the Analytic Hierarchy Process to model the adoption decision process for future scanning and optimizing technology in hardwood sawmills. Data was collected through personal interviews with two hardwood sawmill groups including adopters and non-adopters of advanced scanning and optimizing technology. The interviewee rated the importance of the decision factors in the adoption decision process. They also rated the influence of four sawmill departments on the adoption decision process.

The results from the mail survey found that the average yearly lumber production was 7.6 million board feet per sawmill. The most common type of scanning and optimizing technology, headrig optimization, was only in use by 27 percent of the responding mills. Advanced scanning and optimizing technology such as edger-optimizers and trimmer-optimizers were only in use by 10 percent and 5 percent of the respondents respectively. Adoption decision factors for scanning and optimizing technology were rated. *Improved raw material recovery* and *increased lumber revenues* were the two most highly rated factors. *Accuracy of grading* was the most highly rated factor for automated grading systems. The adoption decision model found that production related issues were most important in the decision process and that the production department was the most influential of the sawmill departments.

Overall, scanning and optimizing technology adoption within the hardwood sawmill industry is low. For those that have adopted advanced scanning and optimizing technology, production issues were the driving factors.

DEDICATION

In loving memory of my father, Orville Joseph Bowe, who was not here during my time in graduate school, but would have been proud of my accomplishments. For my mother, Doris, and my brothers and sisters, Debbie, Greg, Pat, Deonne, and Denise. I look forward to spending more time with my family in Wisconsin. And for Jackie, who felt I was worth waiting for.

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PREFACE

This dissertation is broken into five chapters. Chapter 1 defines the problem, organizes objectives to address the problem, and reviews the literature important to the research. Chapter 2 describes the methods and results of the mail survey which examined the current state of the hardwood sawmill industry. Chapter 3 further examines the mail survey and focuses on scanning and optimizing technology within the hardwood sawmill industry. Chapter 4 examines a modeling method for looking at the adoption decision process for future scanning and optimizing technology within the hardwood sawmill industry. Finally, Chapter 5 summarizes the overall findings and presents a personal perspective of the hardwood sawmill industry.

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CHAPTER 1: Introduction and Literature Review

Introduction

"You don't have to change, survival is not mandatory."
W. Edwards Deming

The forest products industry is not well known nor well understood by the general public. Much of the public is unaware of the industry's size or its impact on the domestic economy. The United States uses over 510 million cubic meters of wood each year (Haygreen & Bowyer 1996). In 1998, lumber sales alone were estimated at $18.3 billion (Cited in Kincaid 1998). From another perspective, the weight of wood used each year in the United States is roughly equivalent to the weight of all metals, plastics, and portland cement ***combined*** (Bowyer 1992). Within the last thirty years, however, environmental concerns and increasing demand for wood products have brought the forest products industry into the public's view. In order to satisfy the public's concerns and demands for wood, the forest products industry needed to act on two fronts. First, it had to step from the shadows and defend itself against the public's environmental accusations (correct or unfounded). Second, it had to meet the public's increasing demand for wood products. Consider a historical analogy: In the early years of sawmilling, sawmill equipment consisted of two people and a bow saw. One person stood below in a pit while the other person stood above with the log. The bow saw was powered by hand to cut boards from the log. The advent of mechanical means to power the bow saw and the later introduction of circular and band saws were major technological steps in sawmilling that radically increased production to meet demand.

Today, equally significant technological leaps are being introduced to the forest products industry. The industry is producing new products such as engineered wood. It began using new production methods such as optimizing technologies. The industry also learned to use underutilized raw materials, as well as a changing raw material base. Not only do these new technologies help meet the demand for wood, but these technologies also provide improved efficiency of raw material use.

As a part of this greater industry wide change effort, hardwood lumber producers are also facing change; however, hardwood lumber producers are very resistant to change or do not see the need to change. It is common to find sawmills that use technology over a half a century old. The demographics of the hardwood sawmill industry may in part drive this reluctance to adopt new technology. Estimates from the National Hardwood Lumber Association's (NHLA) member and nonmember mailing lists suggest that there are over 4,300 hardwood sawmills in the United States. Of these, many are small companies. Companies of this nature may not have the capital or the supporting market share to justify purchasing high technology equipment. Estimates from the *Weekly Hardwood Review* suggest that the 50 largest sawmills only represent 15 percent of the total hardwood production with no single company producing more than 1.5 percent (Cited in Kincaid 1998). A significant number of large and medium mills do exist, however, and are a potential market for hardwood sawmill technology.

It is important not to underestimate the hardwood sawmill industry's importance. Estimates for 1998 place U.S. hardwood production at 13.5 billion board feet (Hansen & West 1998). This represents approximately $8.1 billion for rough green lumber (Araman 1999). Of this volume, approximately 6 billion board feet is considered high quality grade lumber (Kincaid 1998). This high quality grade lumber forms the foundation for numerous other value added industries such as the furniture industry and the cabinet industry. For example, 1998 estimates suggest that the furniture industry used 3.8 billion board feet of hardwood lumber. Cabinets alone accounted for over 276 million board feet (Hansen *et al.* 1995). In addition, 4.8 billion board feet of low grade hardwood lumber was used in the pallet and container industry in 1993 (Reddy *et al.* 1997). This translates roughly into a $2.31 billion dollars in hardwood pallet sales alone (Reddy *et al.* 1997; Mitchell 1999).

Despite the limited adoption of technology in the hardwood sawmill industry, new manufacturing technology is not completely absent. A few innovative companies have implemented scanning and optimizing technology. With scanning and optimizing, the same basic sawmill structure exists (Figure 1-1), but key elements have been adapted to accommodate the new technology. Headrig, resaw, edger, trimmer, sorting, and grading have all been adapted at various levels to use scanning and optimizing technology. From an environmental perspective, scanning and optimizing technology is designed to utilize the raw material more efficiently. From a business perspective, scanning and optimizing technology is designed to produce higher grade yield, quality, and consistency which leads to higher profit margins for the sawmill. Ultimately, scanning and optimizing technology satisfies the public's demands to utilize our natural resources more efficiently while increasing production efficiency to meet demand.

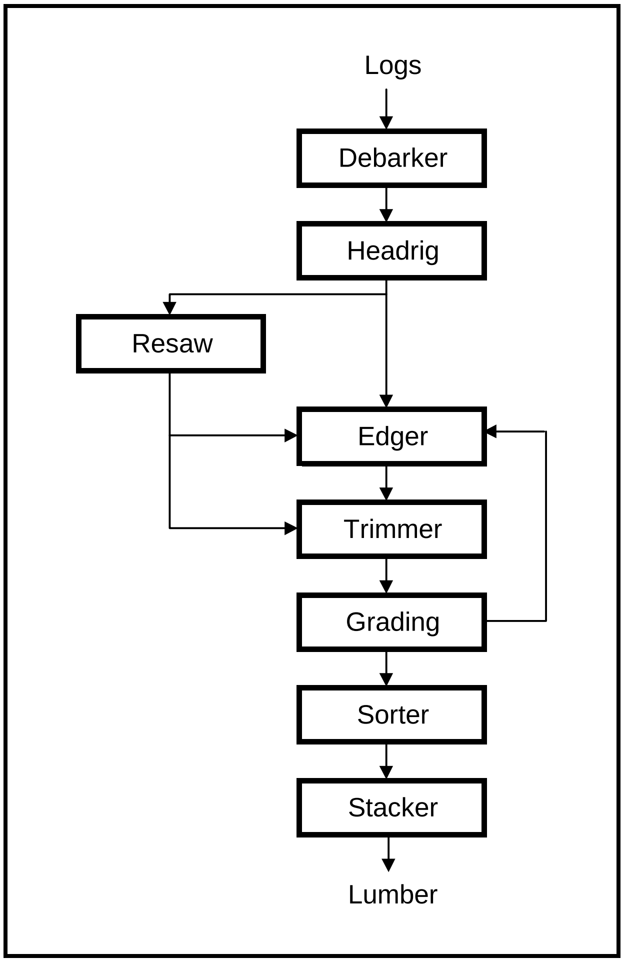

Figure 1-1: Schematic of Production Flow in a Typical Hardwood Sawmill

Hardwood lumber producers are slowly adopting this technology change effort; however, scanning and optimizing technology is still not clearly understood. What are its advantages in production? What are its advantages in the market place? How do sawmill managers decide if scanning and optimizing technology is the correct choice for their mill? Left unanswered, these questions will further delay the potential benefits of scanning and optimizing technology.

Problem Statement

The existence of several manufacturers of commercial hardwood lumber scanning and optimizing technology suggests that there is a market for this equipment; however, this market is not well developed. From the hardwood perspective, we are calling scanning and optimizing technology new technology, yet various levels of this technology have been used in the softwood industry in some capacity for some time. In the hardwood sawmill, however, the adoption and use of scanning and optimizing technology is less prevalent. This lack of adoption may stem from technological difficulties in translating this technology from the softwood mill to the hardwood mill. Slow diffusion may also stem from the lack of quality information supporting scanning and optimizing technology. It is necessary now to understand the factors that will lead hardwood sawmills to adopt *new ideas* such as scanning and optimizing technology. These technologies have been adopted by softwood mills with success. Such equipment has become the standard rather than the exception in the softwood lumber manufacturing industry. Scanning and optimizing equipment provides users with a more uniform and a higher quality product. Of critical importance is the technology's ability to generate a higher valued product with the same raw material. Technologies such as scanning and optimizing technology are paramount in satisfying the growing world population and its growing demand for wood products. Forest health and stability will benefit from these technologies.

The *newness* of scanning and optimizing technology is a combination of adapting it from the softwood industry to the needs of the hardwood industry and engineering the scanning ability to much higher levels. Here, several problems arise because the sawmill customer is not understood. First, the differences between those companies that adopt scanning and optimizing technology and those companies that do not adopt scanning and optimizing technology are unknown. From a marketing perspective, these differences need to be identified to better define the market. Second, several manufacturers produce scanning and optimizing technology systems yielding similar yet different benefits. From this, many different system designs and levels of implementation (new mill or retrofit) exist with this technology which ultimately leads to confusion with the varying levels of installation costs and system benefits. Third, within this confusion, the expectations, goals, and objectives of the hardwood lumber industry with respect to scanning and optimizing technology are not understood. This will be valuable in assessing the potential market for the current and next generation of scanning and optimizing technology. Finally, the decision process that a company uses when considering scanning and optimizing technology must be better understood. This understanding will allow for a systems view into scanning and optimizing technology adoption. This systems view enables an organization such as a hardwood sawmill to examine and identify how scanning and optimizing technology fits into the whole organization (raw material, production, marketing, and customers) rather than a limited production only view.

This research will provide scientists and developers of this technology with needed information to assist in the development and adoption of scanning and optimizing technology. Ultimately, adoption of this technology will provide higher grade yields and more efficient use of the log to best utilize our renewable natural resources.

Finally, since scanning and optimizing technology can include many production components in a hardwood sawmill, this research will focus on three specific groups including **current** scanning and optimizing technology, **advanced** scanning and optimizing technology, and **future** scanning and optimizing technology. **Current** scanning and optimizing technology is an all-encompassing term. It includes all of the currently available scanning and optimizing systems such as *bucking-optimizers*, *headrig-optimizers*, *edger-optimizers*, *trimmer-optimizers*, *grade mark readers*, and *automated sorting* systems. **Advanced** scanning and optimizing technology is more specific. It refers specifically to the most advanced and innovative systems currently available. These systems only partially optimize since decisions are based on profile information only (size and wane). These systems include edger-optimizers and trimmer-optimizers. Finally, **future** scanning and optimizing technology refers to prototype systems that are not commercially available. This technology is more advanced since it truly optimizes based on total defect information (profile, knots, splits, etc.). An example of this technology is the Auto-Grade system under development at Virginia Tech (Kline *et al.* 1998). Future references to scanning and optimizing technology will specifically imply these three groups (Table 1-1). Research on these groups will complement ongoing research at Virginia Tech.

Table 1-1: Types of Scanning and Optimizing Technology

Current Scanning and Optimizing Technology
Bucking-optimizers
Headrig-optimizers
Edger-optimizers
Grade Mark Readers
Trimmer-optimizers
Automated Sorting Systems
Advanced Scanning and Optimizing Technology
Edger-optimizers
Trimmer-optimizers
Future Scanning and Optimizing Technology
Edger-optimizers
Automated Grading Systems

Many optimization systems within the hardwood sawmill focus on volume recovery. It is important to note that advanced and future scanning and optimizing technology focus on optimizing value recovery.

Objectives

From the problem statement, the following three objectives have been defined:

1. Determine the differences between company characteristics for both adopters and non-adopters of scanning and optimizing technology.

2. Identify company expectations of scanning and optimizing technology: cost and feature levels of scanning and optimizing technology systems that will be accepted by the hardwood lumber industry.

3. Using the Analytic Hierarchy Process, examine sawmill management's scanning and optimizing technology adoption decision process based on a sawmill system's perspective.

Literature Review

Scanning and Optimizing Technology Background

When we speak of technology changes or advancements in the hardwood lumber industry, we are largely speaking of scanning and optimizing systems in the hardwood sawmill. The purpose of scanning and optimizing technology is to replace or assist a human operator with the decision-making processes when manufacturing hardwood lumber. Scanning technology refers to vision systems that use cameras, lasers, x-ray, ultra sound, or other sensing mechanisms to *see*. In the case of a hardwood sawmill, several current systems use lasers to generate a profile image of a log or board. The *seeing* is only the first part of the scanning task. The system must also integrate the appropriate software to interpret what it is seeing and finally use this information to optimize production. This usually consists of some type of automated processing system that utilizes the optimized vision data (Figure 1-2).

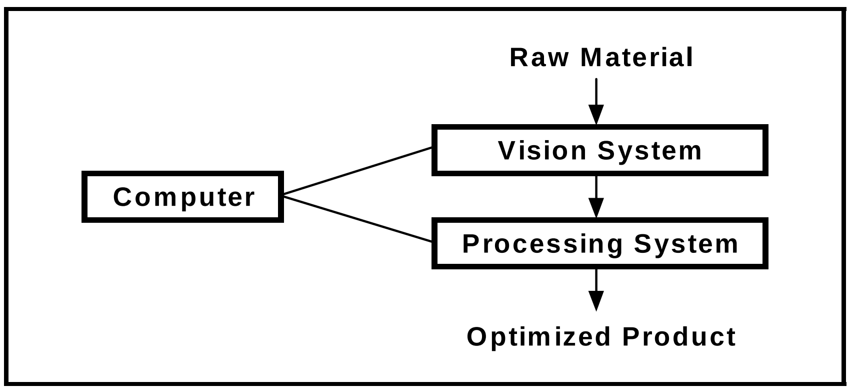

Figure 1-2: Scanning and Optimizing Systems Flow Diagram

Scanning technology at the sawmill can come in many different forms. Whether a sawmill has scanning technology or not, the basic mill structure is the same. Scanning systems can be fitted to several of the sawmill's components (recall Figure 1-1). The headrig can utilize computerized set works and scanning positioning systems to optimally position the log before it is sawn. Edging and trimming systems can utilize scanning and optimizing systems to locate and identify defects for optimal processing. Automated scanning grading systems are being tested which eliminate human fatigue and error in the grading process. Finally, sorting systems and automated color sorting systems utilize scanning technology.

Scanning technology in the form of linear positioners on the headrig carriage have been used extensively in the softwood industry since the 1970's (CME 1998). Since that time, scanning technology has expanded from the headrig to include edging, trimming, and other systems in the softwood sawmill. This technology has become a standard in most softwood mills (CME 1998). It is important to note, however, that this technology has not diffused to the same degree in the hardwood mills. One possible explanation for this is the non-uniformity of hardwoods compared to softwoods. For the most part, defect free wood in softwoods is very light and uniform in color. Defects in softwood (knots, splits, etc.) are very distinct, usually very dark in color, and are usually very uniform determined by the physiology of softwood trees. This contrast between dark and light makes defects relatively simple to locate and identify for automated scanning systems. Hardwoods, in contrast, come in a spectrum of colors and have a variety of defect colors and shapes which make isolation and identification by automated scanning difficult.

The History of Scanning and Optimizing Technology Development

The following examples examine the history of scanning and optimizing technology in the wood products industry. These examples are not necessarily specific to the hardwood sawmill and include examples from the softwood industry and the hardwood rough mill. However, the examples show how scanning and optimizing technology was developed and demonstrate the obstacles encountered during development.

Rickford (1987) points out that the first functional optical scanning system was called *eyeballing*. The near infinite complex human brain, eyes, and judgement makes it a formidable scanning system; however, fatigue, feed rates, and experience often render this system far from optimal.
Before the use of scanning systems to locate and identify specific defects such as knots and checks, line scan cameras were used to map the profile of boards. This information is important in processing decisions (Rickford 1987). Other early systems such as area array image sensors built a two dimensional image of boards (Rickford 1987).

Lumber scanning was first conceptualized in the late 60s and early 70s. As they are today, yield, recovery, and value were important in the sawmill operation. Huber (1971) conceptualized using defect detectors, computers, and no kerf cutters (lasers or water jets) to remove defects in lumber. Even though the technology for defect detection or no kerf cutters was not yet available, yield under such systems could produce a ten percent yield increase (Huber 1971). Huber conceptualized his system with the following schematic (Figure 1-3):

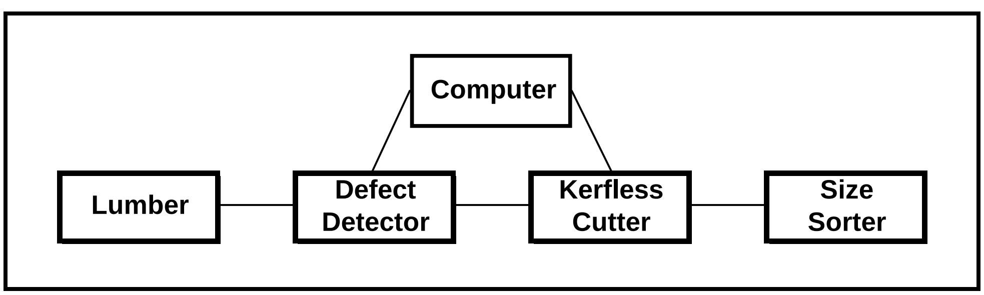

Figure 1-3: Conceptualized Lumber Scanning System (From Huber 1971)

Other early work on image analysis and defect detection was performed by McMillin (1982). Using a video camera and a computer system, McMillin was able to use the computer to make measurements from the video input. From this, applications in defect detection in solid wood products, particle geometry and orientation in composite products could be developed. In addition, applications in quality control and machining would be advantageous in the wood products industry (McMillin 1982).

By the late 70s and early 80s, significant advances in the defect detector systems were made. Systems using optical, ultrasonic, microwave, x-ray, and neutron detectors were being researched (Szymani & McDonald 1981). However, functionality and impracticality soon made Huber's simplistic defect detector component a serious challenge. In Szymani and McDonald's review of these technologies, they found complications with each system. Optical systems such as cameras and lasers were limited to surface defect detection only. Ultrasonic, microwave, x-ray, and neutron systems could detect internal defect but could not differentiate color (Szymani & McDonald 1981). These results suggested that a system utilizing several of these detectors types would be better than using only one type of detector.

By the early 1980s, more complex scanning systems were proposed. In addition to scanning lumber for defect, McMillin *et al.* (1984) suggest scanning the log to determine optimal breakdown. The Automated Lumber Processing System (ALPS) utilized computerized axial tomography to locate internal log defects. From this interior mapping, optimal yield or value log breakdown patterns could be determined. After the log was processed, the boards would be dried and planed. The proposed ALPS would scan the boards with a video camera. This video information was digitized and analyzed by computer to locate and identify defects. This information could then be used to develop an optimum cutting strategy (McMillin *et al.* 1984). As with earlier proposed systems, lasers could be utilized by ALPS to minimize kerf and optimize useable material (McMillin *et al.* 1984). Lasers would have an advantage over conventional ripsaws and crosscut saws since defects could be removed in a cookie cutter fashion. Saw systems must make a complete pass across or down the length which uses more material.

A more recent article from 1993 examines the ALPS system ten years later. This paper specifically mentions the use of this technology for hardwood lumber (Klinkhachorn *et al.* 1993). Like the earlier system, this pre-prototype uses a computer vision system to scan and identify defects. From this, computer programs can assign NHLA grades and produce optimized cutting bills. Like the earlier system, a proposed laser cutting component provided for kerfless breakdown (Klinkhachorn *et al.* 1993).

As with the earlier vision systems, ALPS optical detector (gray-scale camera) had several problems to overcome. Grain marks, color variations between heartwood and sapwood, and variations in texture complicate defect identification (Klinkhachorn *et al.* 1993). These complications directly affected the grading and optimizing functions of ALPS. A neural network computer system was implemented to process the camera information and deal with these input complications (Klinkhachorn *et al.* 1993). Correct identification and location of defects are necessary for assigning NHLA grades and cutting bills for yield or value optimization.

At the time of the report, the vision system could process up to ten lineal feet per minute with a defect detection accuracy of greater than 95 percent (Klinkhachorn *et al.* 1993). Advances in computer processing speeds and image capture were needed to increase to real-time processing.

Pham and Alcock (1998) reviewed automated grading and defect detection in one of the most current articles published on this topic. Building on Huber's original concept, Pham and Alcock suggest a scanning system scenario called the Automated Visual Inspection System (AVI). AVI consists of the components shown in Figure 1-3.

Scanning and optimization with a system such as AVI involves several steps. These steps include image acquisition, image enhancement, image subdivision, feature extraction, classification, and optimization.

Image acquisition consists of a camera (color or gray-scale), laser, or other detector. When using cameras, lighting is very important to produce the highest quality image. Image quality ultimately affects the system's defect identification ability. Research has found color images to be superior to gray-scale images in defect detection (Cited in Pham & Alcock 1998:31 & 48). Color images were also shown to add computational burdens to the system (Cited in Pham & Alcock 1998:5). Detector arrangement is also an issue. Top, bottom, and side-mounted detectors as well as multiple detectors are possible arrangements. Proper ventilation and airflow over the detectors must be implemented to keep the detectors dust free (Pham & Alcock 1998). It is difficult to maintain the necessary image quality with the sawdust, dirt, and vibration common to all hardwood sawmills. In addition, complex technology requires highly trained personnel for maintenance and repairs.

Image enhancement involves further differentiation of clear wood and wood with defect. This is done by accentuating the defects to increase the differentiation (Pham & Alcock 1998).

Image subdivision consists of breaking the image down into regions of the same type (clear wood and defect wood). Two approaches to this are *local* and *global* (Cited in Pham & Alcock 1998:68). The local approach consists of breaking the image down into a grid, such as individual squares. A problem with this system was that as you decrease the size of the squares, computational costs increase. The global approach used segmentation to separate the wood image into meaningful categories (clear wood and defect wood). This results in irregular shaped boxes defining the boarders of the defects (Pham & Alcock 1998).

Feature extraction applies feature to the objects identified in image subdivision. Features often describe shape, size, and intensity levels of the object.

From the feature information, *classification* assigns what type of defect the object is (Pham & Alcock 1998). For example, with certain object size, shape, and gray-scale intensity, the program may identify the object as a knot.

Optimization occurs after the defects are located and identified. Grade or cutting bill information can be generated in an optimal manner with complete defect information. Optimization is a major value in AVI systems.

From this review, several conclusions are found. Hardware scanning technology in cameras, lasers, x-rays, etc. exist and can be used satisfactorily in a manufacturing setting to scan and capture an image of a board. The more difficult task lies in developing the software for defect recognition. Lumber defects come in an infinite array of shapes, sizes, colors, and arrangements. The software must be able to differentiate the defect from clear wood and classify the defect by type. Recognition is the weakest link. After recognition, grading or cutting bill software can identify optimal breakdown depending on final use.

Adoption History of Scanning and Optimizing Technology

The previous sections examine the history of scanning and optimizing technology development. From this, it is interesting to examine how this technology was adopted into the forest products industry.

The first edge-optimizer system to be installed in the United States was in 1976. Weyerhaeuser Co. installed the system in one of its Oregon softwood mills. The manufacturer of the edger-optimizer system, Saab-Totem Inc., was a Swedish-American joint venture (White 1977). The system claimed 92 percent recovery compared to 70-85 percent recovery with a human edger.

From this early beginning in sawmill optimizing, the softwood industry has embraced scanning and optimizing technology which has become the norm. Saunderson (1982) suggests that falling operational margins drove the adoption of scanning and optimization equipment. In the early 1970’s, operating margins were 25-30 percent of net sales. These margins fell below 10 percent by 1979. To stay competitive, the entire softwood sawmill industry had to follow suit.

In contrast, however, the hardwood sawmill industry has not adopted scanning and optimizing technology as quickly as the softwood industry has. Certain types of scanning and optimizing equipment have been accepted by the hardwood sawmill such as primary log breakdown equipment. Other technologies such as edger-optimizers and trimmer-optimizers have been slow to adopt. The first edger-optimizers began to appear in hardwood sawmills in the late 1980’s. RAM Forest Products, a hardwood sawmill in Shinglehouse, Pennsylvania, installed the first hardwood edger-optimizer in 1988. This edger-optimizer, developed by Inovec, Inc., used NHLA wane and size rules in its optimizing program. Since this time, several other manufacturers have developed hardwood edger-optimizer and trimmer-optimizer systems. Integration of this technology into the hardwood sawmill industry has not come close to the successful integration of this technology in the softwood sawmill industry.

Scanning and Optimizing Technology Benefits

Whether a sawmill utilizes scanning and optimizing technology or depends completely on human operators, the boards, once sawn from the log, must go through a process of locating and identifying the defects before the boards can be further processed (Pham &

Alcock 1998). Locating and identifying defects before processing allows for maximum value yield. Grading allows for proper value categorization. Errors in defect location or identification lead to a reduction in maximum value yield. Errors in grading require the use of inspection or re-grading which ultimately lead to unsatisfied customers. With this in mind, Rickford (1987) stated there are only four ways to increase overall profitability in a sawmill:

4. Manipulate product mix to enhance the average selling price of lumber. Generally this means emphasizing grade recovery where possible, and restricting product mix to high recovery, high yield products, log size and quality permitting.
5. Increase lumber recovery through scant sawing, and kerf reduction. This generally means improving positioning accuracy of machine setworks to permit rough green target size reduction, within acceptable falldown limits.
6. Increasing production by motivation, intimidation or whatever technique seems appropriate to the respective mill manager.
7. Reducing variable cost of production. This generally means handing out pink slips at will to cut down on labor costs, or manipulating log cost.

Whether you agree with Rickford's 18th Century management techniques or not, an important fifth point is missing from his list: *Reducing operator error due to misjudgments and fatigue*. In the hardwood sawmill, this is especially important given the complicated NHLA grading rules. Human edging, trimming, and grading misjudgments as well as human fatigue and lack of training play a large role in reducing overall profitability. Scanning and optimizing technology, on the other hand, does not fatigue. Concerns over *misjudgments* in scanning and optimizing technology systems are still a factor; however, producing a consistent judgment may offset the technology's less than perfect accuracy.

In justifying scanning and optimizing technology, consider human error and variation and yield.

Human Error and Variation

Errors in themselves cost money, but what are the common causes of most errors where human operators are concerned? Studies suggest that high rates of production (line speed) are the problem. Planner rates of 600 feet/min and greater are common in softwood mills. Grading with human operators is a tiring procedure. Often, feed rates must be slowed to accommodate the human graders. It has been suggested that 300 feet/min is a more realistic feed rate for human operators (Polzleitner & Schwingshakl 1992).

Production rates in combination with fatigue and boredom cause human operation to fall below optimum. Consider, for example, edger operators, trimmer operators, and lumber graders. Huber *et al.* (1985) suggest that human operators must perform the following five tasks:

1. see and recognize the defects [recognition]

2. have the mental aptitude to properly locate the cuts [calculation]
3. possess the physical strength to position the board manually [positioning]
4. resist boredom and maintain an alert mental attitude [alertness]
5. while looking at one side, remember what the other side looks like [memory]

Failure of one or more of these tasks can result in reduced yield in rough mills. In addition, all of this must be done in a very short period of time (typically less than 5 seconds per board). To further diminish human performance, most rough mills have working environments not conducive to many of these factors (Huber *et al.* 1985).

Huber *et al.* (1985) also suggest that training programs can be helpful in improving performance and yield, but only for a short term of six to twelve months. Often, trainable personnel are promoted or transferred to other areas leaving new and untrained personnel in their former positions. One time training programs are not sufficient to maintain productivity. Nor do they address the problems of fatigue, boredom, or poor working conditions.

When examining human lumber graders, their accuracy falls well below 100 percent. Huber *et al.* (1985) examined six hardwood rough mill graders over three different manufacturing operations. After the authors located and classified the defects in the sample boards, each defect was recorded. The mill graders were then asked to locate and identify the defects on the same sample boards. When compared to the author's score sheet, a composite score of defect location and defect classification of only 68 percent was obtained. A second study by Polzleitner and Schwingshakl (1992) compared their vision system to four human graders. Their trial found that only 55 percent of the boards were graded the same by the four human graders. Their vision system claims a constant and repeatable 95 percent accuracy in grade. A Finish study gave human graders more credit with accuracy rates (in softwood) of 75 to 80 percent (Lampinen & Smolander 1996). A second Finish study suggests similar human grading accuracy rates of 70 to 80 percent; however, it is suggested that the human grader can only perform classification into three to five categories at a time (Silven & Kauppinen 1996).

These findings show two things: first, human grading is below if not far below optimum; second, there seems to be great variation in the performance and the consistency in human graders. The goal and major benefit of scanning and optimizing technology is its ability to improve accuracy in lumber processing and grading and to reduce variation in lumber processing and grading.

Yield

Questions have been raised concerning the most accurate method to measure the benefits of scanning and optimizing technology systems. As described above, scanning and optimizing technology may reduce human errors in lumber production and grading, but what other types of advantages might scanning and optimizing technology provide? Does the scanning and optimizing technology system provide yield advantages, labor advantages, and/or marketing advantages? The metrics in such a question are more difficult to determine than initially thought.

Consider yield for example, Regalado *et al.* (1992-a) suggest that before the benefits of scanning and optimizing technology systems can be understood, the performance of existing human operated systems should be evaluated. In this study, a total of 120 hardwood boards were taken from three different sawmills. From these boards, NHLA grading rules were used to estimate an optimized edging and trimming solution. This solution was compared with the actual solution of the board after it was processed through the mill's edger and trimmer. In the end, value recoveries of 62, 65, and 78 percent of the estimated optimum were found over the three mills.

From both the grading and yield examples, a very important point is made. Even though current scanning and optimizing technology does not locate and identify every defect perfectly, substantial deviations from optimum may still be allowed and the system will perform better than human operators (Huber *et al.* 1985, Pham & Alcock 1998). Under normal grading rules, 80 percent defect recognition can result in 80 to 90 percent grade accuracy (Silven & Kauppinen 1996). This effect was studied by Regalado *et al.* (1992-b) by using varying levels of defect information when generating an edging and trimming solution. The following four levels of defect information were used:

1. wane information only
2. wane, checks, splits, shake, and holes
3. wane, sound knots, unsound knots, and decay
4. wane and the location and size of all defects

When compared to actual values processed at the sawmill, wane information only produced an estimated optimization average of 81 percent of optimum. Wane, checks, splits, shake, and hole information was not significantly different from wane only information. Wane, sound knots, unsound knots, and decay information produced and estimated optimization average of 88 percent of optimum. Complete information using wane and the location and size of all defects generated and estimated optimization average of 95 percent (Regalado *et al.* 1992-b). Recall from the previous study that an average of 68 percent of optimum was generated by human operators at the mill (Regalado *et al.* 1992-a). Many current edging optimizing systems use wane only information to generate their cutting solutions. From this study, it can be safe to assume that these systems will perform at less than optimum given variation and error in the vision and optimizing systems.

It is only reasonable that an automated system can produce better yield and consistency than a human grader if the system has 100 percent accurate defect information. What may be surprising and is clearly demonstrated above, however, is that scanning and optimizing technology systems can produce consistently higher accuracy with less than perfect information.

Commercially Available Scanning and Optimizing Systems

Initial literature searches and trade show interviews found over ten commercial manufacturers that develop lumber scanning and optimizing systems or at least primary system components. Closer analysis found that only eight of these companies produce scanning and optimizing technology (primary edging and trimming systems). Table 1-2 describes the most current manufacturers and the systems that they produce. This list changes almost monthly, however. Frequent company mergers and closings describe the unstable nature of this market. Several of the companies listed in Table 1-2 are developers of both primary and secondary hardwood processing equipment. In addition, they produce technology for softwood processors as well as hardwood processors.

It is important to note that the commercially available systems listed in Table 1-2 use lasers to collect defect information. Lasers are only able to collect size and wane information from the scanned boards. From this, only *partial optimization* is possible given the incomplete defect information collected.

Table 1-2: Current Commercial scanning and optimizing technology Manufacturers

Company	Product	Vision Technology
Coe Manufacturing Co.	D*Tec Edger-optimizer D*Tec Trimmer-optimizer	Laser
Inovec, Inc.	TrimMaster™ Hardwood Trimmer-optimizer WaneMaster™ Hardwood Edger-optimizer	Laser (DynaVision™)
Hi-Tech Engineering, Inc.	Hi-Tech Optimized Edger System Hi-Tech Optimized Trimmer Sorter System	Laser (DynaVision™)
USNR	Edger-optimizer System Accutrim™ Trimmer-optimizer System	Laser
Perceptron, Inc.	Edger-optimizer System Trimmer-optimizer System	Laser
Paul Saws & Systems	Edger-optimizer System Trimmer-optimizer System	Laser
Corley/Lewis Controls	Edger-optimizer System	Laser (DynaVision™)
Dynamic Systems Group, Inc.	DynaVision™ Laser Component	Laser

Adopting Scanning and Optimizing Technology and the Sawmill System

When a company considers purchasing a scanning and optimizing technology system, they are considering making a fundamental change to how their organization operates. Implementing scanning and optimizing technology is specifically related to a production process change. However, a change in the production process will undoubtedly affect the whole *sawmill system*. For the most part, however, this organizational system affect is not understood. This lack of understanding of scanning and optimizing technology and the sawmill systems may result from the *newness* of this technology. Also, it could be that no one has yet to ask questions about the system as a whole. Understanding the decision, adoption, and change process as they relate to scanning and optimizing technology and the sawmill system will benefit the hardwood lumber industry.
Deming (1993) defines a system as follows, “A system is a network of interdependent components that work together to try to accomplish the aim of the system.” Past and current research has considered scanning and optimizing technology’s effect on the production process only. Using *systems thinking*, an examination of scanning and

optimizing technology's effect on the entire sawmill system can be performed (Figure 1-4).

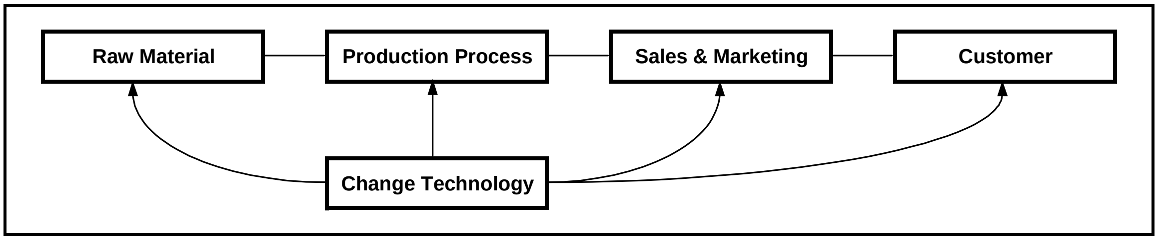

Figure 1-4: A Sawmill from a System's View

How does scanning and optimizing technology affect raw material use and supplier relationships? How does scanning and optimizing technology affect marketing strategies and customer relationships? How does scanning and optimizing technology affect customer attitudes and future purchases? Answers to these system wide questions will help fill the information void now present in the scanning and optimizing technology industry.

Recent management research has used systems thinking as a foundation. Management processes, organizational improvement processes, and measurement processes all use systems thinking. This scanning and optimizing technology research proposes an examination of systems thinking as is relates to the adoption decision process of scanning and optimizing technology. An excerpt from Kaplan and Norton (1996) states:

> Companies that compete in industries with rapid technological innovation must be masters at anticipating customer's future needs, devising radical new product and service offerings, and rapidly deploying new product technologies into efficient operating and service delivery processes. Even for companies in industries with relatively long product-life cycles, continuous improvement in process and product capabilities is critical for long-term success.

Kaplan and Norton (1996) in their book, *The Balanced Scorecard*, stress the importance of systems thinking and innovation in organizational management. They recommend a *balanced scorecard* within an organizational system. Kaplan and Norton could not have described the hardwood lumber industry better with their mention of continuous process improvement despite the existence of long product-life cycles. In the hardwood sawmill, scanning and optimizing technology in combination with systems thinking in organizational management may provide for the long-term success of the industry.

Kaplan and Norton's (1996) balanced scorecard incorporates four perspectives in organizational management including the financial perspective, the customer perspective, the internal-business-process perspective, and the learning and growth perspective. All four components are key in organizational management. In the case of this scanning and optimizing technology research project (Figure 1-4), the hardwood sawmill's raw material component, production process component, marketing and sales component, and the customer component should be viewed as key components in the decision process of adopting scanning and optimizing technology.

This systems thinking approach to organizational management is in the forefront of management research. An organization is no longer viewed as an arrangement of individual components, but rather a continuum of interdependent components. When viewed as a system, it is possible to optimize an organization as a whole rather than attempting to optimize each component at the expense of other components (sub-optimization). The balanced scorecard is one common systems thinking management technique.

Organizational improvement processes have also used systems thinking as a basis. Organizational improvement methodologies such as the *Strategic Performance Improvement Planning Process* (Sink & Carter) and the *Transformation Methodology* (Van Aken *et al*. 1999) are founded on the principle that organizations are system based, and systems thinking is necessary for an organization to be successful.

Systems thinking is also prevalent in the area of organizational performance and measurement. Sink and Tuttle (1989) suggest that systems thinking is critical in designing an effective organizational measurement system. To compile credible organizational measures such as effectiveness, efficiency, quality, productivity, and innovation, the entire organizational system must be considered. Sink and Tuttle's model of an organizational system includes the following components:

1. upstream system
2. inputs
3. transformation process
4. outputs
5. downstream system

Again, this systems thinking scenario in not unlike the hardwood sawmill system (Figure 1-4). Systems are important in organizational performance and measurement. Likewise, systems are important in decision-making.

To better understand implementing scanning and optimizing technology in a system, a review of basic decision and change processes follows.

Decision and Change, A Review

The adoption of scanning and optimizing technology can be considered a change methodology in a sawmill. A change methodology is an improvement technique such as management restructuring, production process improvement, or employee team restructuring. In general, *change methodologies* refer to change processes applied to an organization. These could include changes in management, organizational structure, or processes. Examples include Total Quality Management, Reengineering, or scanning and optimizing technology adoption. The goal of any change methodology is the improvement of the system it is applied to. The literature reviewed in previous sections examined the theoretical yield benefits and the theoretical human benefits of scanning and optimizing technology; however, published research examining scanning and optimizing technology in a working hardwood sawmill environment is absent. In addition, a broader view of the scanning and optimizing technology's affect on the sawmill system as a whole has not been examined. As with many products, the technology is developed before its public acceptance and intended environment is fully understood. Given this lack of change information specific to the hardwood sawmill, it is interesting to examine more general change information. Consider two basic components to the adoption and change process: diffusion and decision.

Diffusion

When change and technology are examined, they are often measured in terms of diffusion rate. Technology success is often a direct result of the diffusion process. What factors, however, influence the time scale of the diffusion process? Consider information and economics.

Swan (1995) suggests that firms without a complete or sufficient knowledge base will find innovation difficult. Rosenberg *et al.* (1990) supports Swan's suggestion by listing four reasons for slow adoption of technology in the forest products industry:

1. fragmented information on technology
2. slow addition of relevant information
3. ineffective feedback loops for information in the forest products industry
4. scientific theory can not answer all technology specific questions

Building on Rosenberg's information shortcomings, benefits of new technologies are often exaggerated or at least overstated. As long as the gap between actual and stated is large, resistance to adopt a new technology should not be dismissed as slow or lagging diffusion (Rosenberg *et al*. 1990). To go further, lack of comparison of benchmark data gives decision-makers little hard information to base their decisions on. All of these points can be directly compared to scanning and optimizing technology.

Rosenberg *et al.* (1990) suggests that slow diffusion rates may also indicate poor economic conditions rather than internal conservatism:

> Decisions to develop and adopt new technologies are ultimately based on economic and not purely technological considerations. Even though new technologies posses attractive features or reduce the cost of a specific material, the technologies are often not economically superior because all associated costs have not been considered.

The associated costs often arise in parts of the organization outside of the new technology component. The new technology may demand new requirements from suppliers, or new methods of sales and marketing. When considering any new production technology, an organization must ask the following question. How is changing the production process going to affect the total system?

Technology change is also influenced by competition from competing products and changing cost structures in manufacturing (Rosenberg *et al*. 1990). Examples include changing from plywood to flake composite panels because of cheaper raw materials. Wood products firms that traditionally made plywood were forced to adopt flake composite panel technology to maintain panel market share and to remain competitive. The success of the panel industry forced paper companies to adopt papermaking technologies that utilized hardwoods in addition to softwoods. Here competition for raw materials drove the change. These examples show that the diffusion of technology can be driven by competition within and competition between industries. Today, many hardwood sawmills are competing with massive chip mills for their log raw material. It is too early to determine the effect of this competition on scanning and optimizing technology, but it may influence scanning and optimizing technology's diffusion. Research institutions are currently examining the chip mill and hardwood sawmill dilemma. No matter the outcome, hardwood sawmills will be forced to look for better ways to stay competitive.

Decision as a Process

When we think of change methodologies, we immediately think of the physical diffusion and adoption processes or how the change methodology is implemented. There is a larger perspective to examine though. What is the decision process that managers go through before they decide to adopt a change methodology? In addition, exactly who is doing the deciding?

In the decision process, individuals or groups can be the decision-makers. On an individual basis, the decision-maker can proceed without interruptions or roadblocks from other decision-makers. The decision process in an industrial setting is more complex than an individual decision process. In many industrial settings, groups of people have input on the decision to adopt a new technology (Ozanne & Churchill 1971). In other words, each individual must make an essentially independent decision before the group decision is determined. Dimnik and Johnston (1993) examined the dynamics of groups in the decision process. Manufacturing managers move through the decision process by familiarizing themselves with the process (individual decision). If convinced with the merits of the technology, they may become the champions of the technology working for its final adoption by the group.

Whether in a group or individual decision environment, there are many models that describe the decision to adopt process. As an example, consider the following adoption decision model (Ozanne & Churchill 1971):

1. awareness
2. interest
3. evaluation
4. trial

5. adoption or rejection

As a decision process, this model goes beyond implementation and considers factors that precede implementation. Information is a key factor in this decision model. Awareness, interest, and evaluation all depend upon amount and value of information available.

Ozanne and Churchill (1971) discuss another model with five dimensions in the adoption decision process:

1. activating factors (burning platform)
2. purchase directing factors (characteristics that distinguish one technology from another)
3. duration of the adoption process
4. alternative purchases considered
5. information use (sources: personal, advertising, technical studies, etc.)

This model also addresses the value of information, but includes a very important change factor: activating factors or a burning platform. A burning platform within an industrial setting may first spark awareness and interest in a new technology or change innovation.

A third adoption decision model presented by Muth and Hendee (1980) lists five characteristics that influence decision:

1. relative advantage (Is the new better than the old?)
2. compatibility with attitudes, values, beliefs, and needs of adopters
3. complexity of the innovation (Is it easy to understand and use?)
4. trialability (Can it be implemented a little at a time?)
5. observability (Can the innovation's affects be seen?)

Two very important components in this model are compatibility within the company and observability. Does the technology or change process work within the company's attitudes, values, or manufacturing system? Can the benefits of the technology be measured? From this, is the company aware of the technology's total effect on the system?

With respect to information, trialability, and observability, sawmills interested in scanning and optimizing technology do not have these benefits. Research on infield systems to validate manufacturing claims does not exist. Trialability is not an option given the great expense and downtime in the technology purchase and installation. Finally, yield and quality benefits could be quantified in an existing scanning and optimizing technology sawmill, but how these benefits interact with the sawmill as a system is another unanswered question.
Clark and Staunton (1989) suggest that technical innovation usually fosters new ideas about technical and organizational processes. These new ideas are yet to be understood and refined with respect to scanning and optimizing technology given the infancy of the technology. To understand the relationship between technology and organizational

decisions, knowledge and cognition must be considered (Swan 1995). Clark and Stanton suggest where failures of technological innovation occur, too much emphasis is placed on the physical technology change and the role of the knowledge and cognition is neglected. The choice to adopt technology then involves cognitive and political processes (Swan & Clark 1992). Technology innovation provides a complex challenge to an adopting organization since it involves both a technology change and an organizational change (Swan 1995). To date, scanning and optimizing technology has focussed on the physical technology change. Change within the organizational system outside of the production process must be examined more closely.

The previous three decision models are useful in that they outline the basic steps involved in the decision process. What they do not do, however, is reveal the critical determinants of a judgement or set of judgements (Nakamoto 1999). Explained in terms of scanning and optimizing technology, what key criteria or attributes will move the decision process in favor of scanning and optimizing technology adoption? A class of models that will identify these determinates are called policy capturing models (Nakamoto 1999). One such model is the Analytic Hierarchy Process (AHP) model. The AHP model can generate quantitative data on the key determinates. From this, an analysis of the decision process can be performed.

AHP Model in Practice

The AHP model is a mathematical theory for measurement and decision-making that was developed by Dr. Thomas L. Saaty during the mid-1970's (Expert Choice, Inc. 1999). The working process of the AHP model is quite simple. A complex decision is broken into a hierarchy. Within this hierarchy, each hierarchy level can be examined. From this breakdown, the most important decision components can be identified through comparison.

Applications of the AHP model are wide ranging. Examples of AHP model applications include design evaluations, technology implementation decisions, and in quality decisions (Expert Choice, Inc. 1999). Specific application examples of the AHP model follow.

The AHP model has been recommended in practice for new product development. Calantone et al. (1999) have recommended the AHP model as a new product screening decision support tool. Although ideas for new products cost nothing, the research and development of new products can be extremely expensive. This is exactly the case with scanning and optimizing technology. Wood processing equipment manufacturers have spent millions of dollars developing scanning and optimizing technology without a complete knowledge of the hardwood sawmill customer’s wants and needs. It is not suggested here that scanning and optimizing technology is a failing technology; however, an in-depth analysis of the decision and development process would have been beneficial. A decision support tool such as the AHP model could have been useful in this process. Even though scanning and optimizing technology is past the initial new product development stage, the AHP model would be useful in future scanning and optimizing technology improvement.

Albayrakoglu (1996) suggests that the AHP model is useful in the justification of new manufacturing technology. Albayrakoglu developed a model that incorporated environmental, organizational, and technological factors of several manufacturing technologies. The AHP model can then be used as a tool for selecting the best-suited technology. Here the model aids the decision process between several technologies. This is not unlike the decision to adopt or not adopt scanning and optimizing technology.

Finally, Wang *et al.* (1998) suggest that the AHP model can be used as a quality function deployment tool. A main idea behind quality function deployment is to translate customer requirements directly into a product's technical characteristics. Here, the AHP model is useful because of its multi-criteria decision-making features.

Overall, the AHP model has been proven in its application to diverse and complex decision scenarios. Below, the AHP model's internal process is examined in more detail.

AHP Model Situation Example

The AHP model uses both quantitative and qualitative data to aid in the decision process. By dismantling a decision, with all of its associated variables, into small manageable pieces, a decision-maker is able to examine their decision process. The AHP model breaks the important components of the decision into a hierarchical structure. A series of pair-wise comparisons within this structure assigns weights to each component of the hierarchy. In this way, the decision-maker can see how each component affected the overall decision.

Figure 1-5 provides an example of the AHP model applied to the future scanning and optimizing technology adoption decision process.

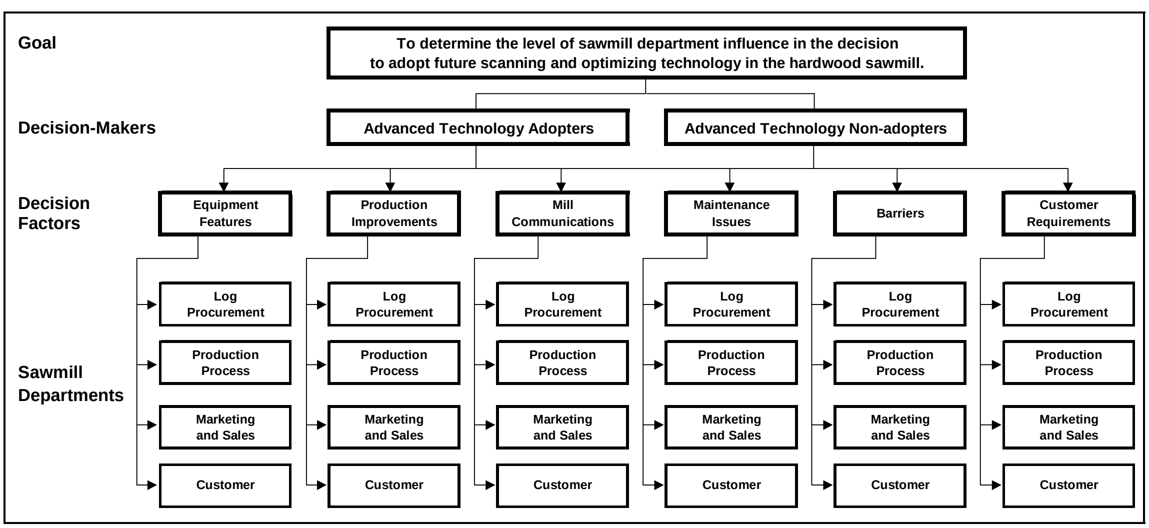

Figure 1-5: AHP Model Example for the Scanning and Optimizing Technology Adoption Decision Process

The model can be broken into four major levels including the *goal* level, the *decision-makers* level, the *decision factors* level, and the *sawmill departments* level. The *goal* level describes the decision under investigation. In the example in Figure 1-5, the model is designed to determine the level of sawmill department influence in the decision to adopt future scanning and optimizing technology in the hardwood sawmill. The second level is the *decision-makers* level. The example shows two groups including advanced scanning and optimizing technology adopters and advanced scanning and optimizing technology non-adopters. Comparison of these two groups will identify key factors to why non-adopters have not adopted. The third level, the *decision factors* level, consist of factors important in the decision process. At this level, a series of pair-wise comparisons are made which weight the relative importance of each decision factor. Level four, the *sawmill departments* level, is key for the sawmill systems analysis. This systems level examines pair-wise comparisons between each sawmill department as they are influenced by each decision factor one level up. For example, when it comes to *equipment features,* which sawmill department is more influential: the *log procurement* or the *production process* department, the *log procurement* or the *sales and marketing* department, and so on (Figure 1-5). From this, we are able to learn which sawmill department is most influential in the adoption decision process for future scanning and optimizing technology.

The AHP model as applied to this research is useful in two important respects. First, it will be used as a behavioral model to model the decision process of scanning and optimizing technology adopters and non-adopters. Second, after the model's development, it will be used as a normative model to aid decision-makers (Smith *et al.* 1995). In other words, if a sawmill is considering scanning and optimizing technology, this model could lead them through an informed and complete decision process.

Expert Choice™ Decision Support Software is designed to run the AHP model in a PC environment. By constructing the decision hierarchy in Expert Choice, the program will calculate the appropriate vectors and matrices as the pair-wise comparisons are being made. Depending upon the decision environment, Expert Choice offers an individual decision-maker format and a group decision-maker format.

Summary

The hardwood lumber industry is an important and large industry. The hardwood sawmill is the foundation of this industry. Scanning and optimizing technology could be an important tool for the future success of the hardwood industry. Much about scanning and optimizing technology is still unknown, however. Limited research examining the theoretical yield, quality, and human benefits of scanning and optimizing technology is found in the literature. Scientific research examining functional scanning and optimizing technology in a sawmill setting has yet to be performed. This lack of information may be a contributing reason for scanning and optimizing technology's slow rate of diffusion. Scanning and optimizing technology has been widely used in softwood sawmills for many years. It is possible that this technology is just further along the adoption time line in softwoods versus hardwoods.

Within any change process, it is important to understand the decision and implementation process.   Leaning how sawmill managers form their opinions and make their decisions about scanning and optimizing technology would answer questions about the scanning and optimizing technology adoption process. This information would be valuable for the sawmills and the technology manufacturers. It would help the sawmill manager to make better decisions and show the technology manufacturer what factors are important to their customers.

As a part of the decision process, it is important to understand the system wide effects of scanning and optimizing technology. It expected that scanning and optimizing technology affect components of the sawmill outside of the production process, but whether or not these system wide effects are considered in the decision process is unknown.   Given this greater system effect, will scanning and optimizing technology fit into a sawmill's current system? Do the benefits of the technology fit into the belief and production system of the hardwood lumber industry as a whole?

Understanding scanning and optimizing technology, how it is implemented, and its total system affect will help the hardwood industry make better choices.

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CHAPTER 2: A National Profile of the Hardwood Sawmill Industry

Introduction

Estimates for U.S. hardwood lumber consumption in 1997 were over 13 billion board feet (Hansen & West 1998). From a value perspective, this volume of rough green lumber would be valued at approximately $8 billion (Araman 1999). Hardwood lumber volume is used to produce many different value-added products including furniture, pallets, cabinets, millwork, and flooring. The final value of these value-added hardwood products would fall into the tens of billions of dollars (U.S. Census Bureau 1999). Hardwood sawmills form the foundation for these markets.

Unlike the softwood sawmill industry with its high production mills, the typical hardwood sawmill is smaller and exists in a more fragmented industry (Hardwood Review 1999-a). Traditionally, hardwood sawmills were small family run businesses. This is beginning to change. Estimates from the NHLA's mailing lists from the 1980's and 1990's place the number of sawmills nationwide at 4300; however, this number is likely an overestimate. Recent consolidation by large hardwood sawmill companies such as Baillie Lumber Co. and Coastal Lumber Co. demonstrate an ongoing trend toward larger and fewer hardwood sawmill companies. Competition for logs along with high log prices favor large companies with sufficient production and capitol to withstand such volatility in the log market (Hardwood Review 1999-b).

These changes, though gradual, have eroded our understanding of the hardwood sawmill industry. It is important to understand this industry because timely market information is essential to the equipment and service industries that supply hardwood sawmills. Second, timely supply information is critical to those companies manufacturing value added products from hardwood lumber. Third, timely market information is important to hardwood sawmills for strategic business and market planning. Finally, timely information is essential for university and government personnel to direct future research and outreach activities targeted at the hardwood sawmill industry.

Objectives

The objectives of this chapter were:

1. Generate a current demographic profile of the hardwood sawmill industry including company demographics and individual respondent demographics.

2. Examine the hardwood sawmill as a system using four components including raw material procurement, production process, marketing and sales, and the customer.

3. Identify the preferred information sources for the hardwood sawmill industry.

Methodology

Population

The population of interest was hardwood sawmills in the United States. Given the nature of the hardwood forest resource in the United States, the majority of the sawmills sampled were in the eastern half of the United States; however, it was not limited to this region.

Sample Frame

Two recently compiled hardwood sawmill mailing lists were acquired. These included the National Hardwood Lumber Association's (NHLA) membership list and a non-NHLA member hardwood sawmill survey list. Since there may be inherent bias in any trade association membership list, it was important to incorporate this second group.

The first mailing list was made up of the NHLA's 1999 members which represented 1200 hardwood industry companies. Of the 1200 NHLA members, approximately 602 companies represented actual hardwood sawmills. All 602 NHLA member hardwood sawmills were included.

The second mailing list was originally generated for a 1998 hardwood sawmill study by the NHLA. The NHLA wanted to determine why various hardwood sawmills were not members. Using Standard Industrial Classification codes and state wood manufacturing directories, the NHLA in conjunction with the USDA Northeastern Forest Research Station, generated a list of 3600 non-NHLA member hardwood sawmills across the United States. For this study, a random sample of 1440 companies was selected from this list. This sample kept the overall mail survey manageable and still provided statistical validity in comparison.

Fortunately, the recent survey performed by the NHLA provided suitable parameters and standard deviations to base this study's sample size on. Hardwood lumber production was a fitting parameter to use. This parameter was identified in the NHLA member database. The NHLA member hardwood lumber board foot (bdft) production standard deviation was 5,693,514 board feet. To achieve a confidence interval with a 90 percent confidence level and a precision of 6 percent (as a percentage of the mean bdft production, 500,000 bdft), the minimum calculated sample size was 351. Based on a comparison with a recent Virginia sawmill survey (production and employee parameters), this sample size was conservative (Alderman *et al.* 1999).

A typical response rate for a sawmill survey is less than 30 percent; therefore, all 602 NHLA member sawmills and 1440 non-NHLA member sawmills were targeted to achieve the desired response. This conservative sample size was expected to raise the confidence and precision levels above the acceptable base.

Data Collection

The mail survey followed the Total Design Method (Salant & Dillman 1994). This involved four mailings. The first mailing (sent in a 10X13 inch envelope) included a cover letter and a questionnaire form. It was mailed first class in September of 1999. The cover letter explained the nature and importance of the survey. It also stressed company anonymity for any information provided. The enclosed questionnaire utilized business reply postage for no cost return mailing for the sawmill. Approximately two weeks after the first mailing, a second mailing, which consisted of a follow-up post card, was sent. The post card thanked the sawmills for their response or urged them to reply if they had not. In October, two weeks after the second mailing, a third mailing was mailed first class to those companies that had not responded. The third mailing (sent in a 10X13 inch envelope) included a revised cover letter and a second copy of the questionnaire. Finally, a fourth mailing consisting of a reminder post card followed one week after the third mailing (Appendix A).

Concerning questionnaire content, the questions were designed to gather timely information on the hardwood sawmill industry. This included questions on company size, production figures, and sales figures. In addition, information was gathered on the respondents' characteristics such as position within the sawmill, age, and trade association affiliation. Finally, Likert scales were used to gather information on sawmill system management and pertinent sources of information. Here a 7 point Likert scale was used with 1 representing *least important* and 7 representing *most important* (Appendix A).

Specific questions within the questionnaire were designed to meet the research objectives. Experts from Virginia Tech and the U.S. Forest Service Southern Research Station assisted in the questionnaire development.

Question types and formats were pre-tested in March at the 1999 Hardwood Lumber Manufacturers trade show in Charleston, North Carolina. During the summer of 1999, the completed survey was faxed to ten hardwood sawmills for final pre-testing. Eight companies responded to the faxes after consistent prodding. Only minor formatting issues were identified and changed during the pre-testing phase.

Data Analysis

The returned questionnaires were examined for completeness and usability. Useable surveys were coded and entered into an SPSS® Statistical Data Analysis package computer spreadsheet. SPSS is designed for survey analysis and readily provides summary statistics and comparison statistics for the various survey responses.

Under the topic of scaling, there is often debate on whether means can be calculated from nominal survey data. The common Likert scale is such an example. In this study, however, it was assumed that the Likert scale was equivalent between nominal data points (thereby representing interval data). This allowed for an analysis using conventional based statistics.

To understand the differences and similarities between groups, comparisons were generated from the questionnaire data. The primary comparisons were made between three group types. These included company size, trade association affiliation, and existing sawmill technology.

Employee numbers were used to define company size. Two general categories, *small companies* and *large companies*, were defined. Companies with 19 or fewer employees were defined as small while companies with 20 or more employees were defined as large. This breakdown was consistent with other research in the wood products industry (Hansen & Smith 1997).

The second comparison group used trade association affiliation. The NHLA was chosen for two reasons. First, the NHLA has historically and currently set the standards and certified hardwood lumber grades. In addition, the NHLA is the largest trade association for hardwood sawmills. Second, our mailing database was segregated by NHLA members and non-NHLA members which made for logical comparisons.

Finally, the third comparison group separated the responding companies by adopters and non-adopters of **current** installed scanning and optimizing technology. This equipment included *bucking-optimizers*, *headrig-optimizers*, *edger-optimizers*, *trimmer-optimizers*, *grade mark readers*, and *automated sorting* (Appendix A).

Results and Discussion

Response

Questionnaires were mailed to 2,042 companies. From these, 212 were returned undeliverable. Undeliverable included companies that have gone out of business or companies that moved without a forwarding address or had an expired forwarding address. Nineteen companies requested by phone or by letter to be removed from the study. This group included companies that were never or were no longer in the hardwood sawmill business. It also included companies that did not wish to participate in the study. One final company was determined to be a duplicate between the two mailing lists. Subtracting these companies from the total number left 1,810 companies as potential respondents.

In total, 600 questionnaires were returned. The first question asked the respondent if their company was a hardwood sawmill. One hundred and seventy answered *No*, while *Yes* was checked by 431 respondents. Seven of the surveys marked *Yes* were deemed unusable due to incompleteness. This brought the total useable level to 424 questionnaires. Our target number of useable surveys was 351. The total adjusted response rate was 23.5 percent (Table 2-1). The adjusted response rate was calculated by subtracting the bad addresses from the total mailing and dividing it into the usable responses.

Table 2-1: Mail Survey Response Figures

	Total	NHLA List	Non-NHLA List
Total Mailed	2,042	602	1,440
Bad Addresses	212	1	211
Removal Request	19	2	17
Returned	600	285	315
Hardwood Sawmill	431	272	159
Unusable	7	1	6
Useable	424	271	153
Total Adjusted Response Rate = 23.5%			
Adjusted Response Rate NHLA Mailing List = 45.3%			
Adjusted Response Rate Non-NHLA Mailing List = 12.7%			

The timing of the returned surveys was also examined (Figure 2-1). Two distinct spikes are apparent after the first and third mailing on 9/2/99 and 10/4/99. One could argue the presence of smaller spikes prompted by the post card mailings, but they are less clear. The post cards were mailed on 9/20/99 and 10/11/99. Figure 2-1 represents the value in using multiple mailing suggested in the Total Dillman Method (Salant & Dillman 1994). These data only roughly represented the return dates since the University post office often held the returned questionnaires for several days before they were forwarded to the researcher.

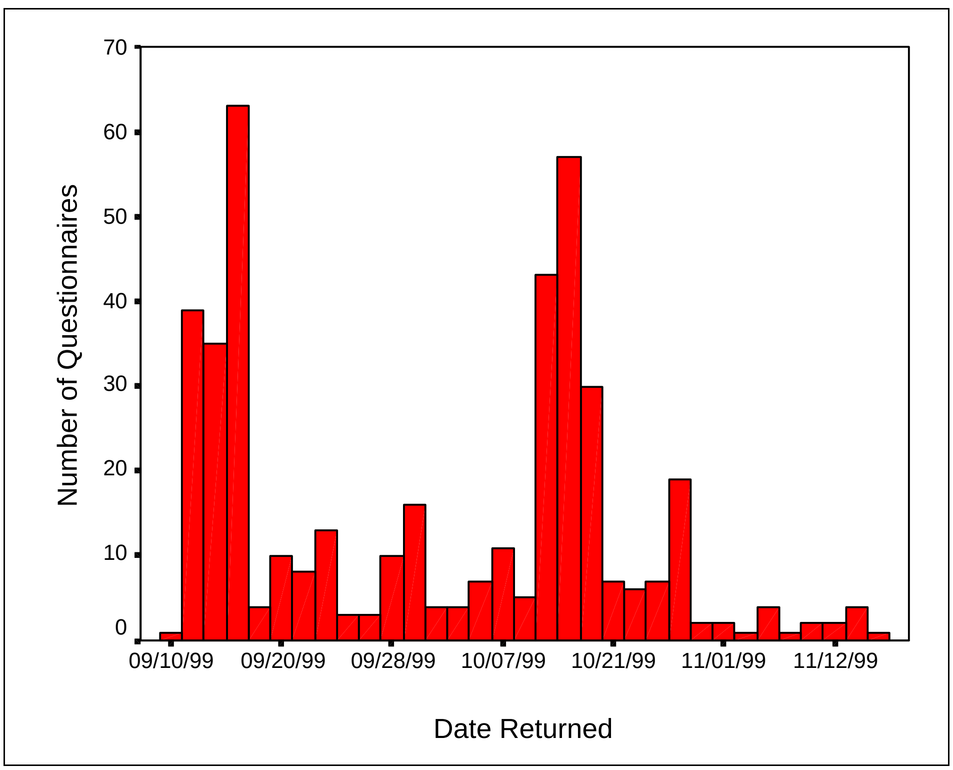

Figure 2-1: Timing of Returned Questionnaires

Non-response Bias

Companies that did not respond were randomly selected, contacted by phone, and asked five questions as they were printed on the questionnaire. A total of 30 calls were completed. Given the sample size, nonparametric statistical methods were used to check for statistical differences between the survey respondents and non-respondents. No significant differences were found between the respondents and non-respondents (Mann-Whitney test, alpha = 0.05).

Demographic Profiles

In order to categorize the information from the hardwood sawmills, several questions collected demographic information. This demographic information was divided into two general categories including company demographics and individual respondent demographics. The following sections explore this information first by looking at the company demographics followed by individual respondent demographics.

Company Demographics

When gathering information on production volumes or numbers of employees, it is important to know if the responding company is providing information for a single operation or providing corporate information for multiple production facilities. This is especially important when trying to extrapolate from sample data to an entire population. Company demographic data is often used as the blow-up factor in these extrapolations.

When asked if their company was a single or multiple facility operation, 283 companies reported being a single facility while 139 companies reported being a multiple facility.

Information on employee numbers was also gathered. Respondents were instructed to report the total number of employees at their sawmill. This was further clarified by asking for the single facility number of employees, not the corporate or multiple facility number of employees.

The mean number of employees was 34.3. The median and mode were 22 and 2 respectively. Employee numbers ranged from 0 to 250. A five percent trimmed mean reduced the mean number of employees to 29.5. A mean is often extremely sensitive to even a single outlier and the median is often extremely insensitive to several outliers (Devore & Peck 1997). A trimmed mean is a compromise between these two situations. In this case, 5 percent of the ordered observations were deleted from each end of the distribution. Companies with large employee numbers were expected since a number of companies had secondary manufacturing in addition to a hardwood sawmill. Figure 2-2 represents the distribution of employee numbers graphically.

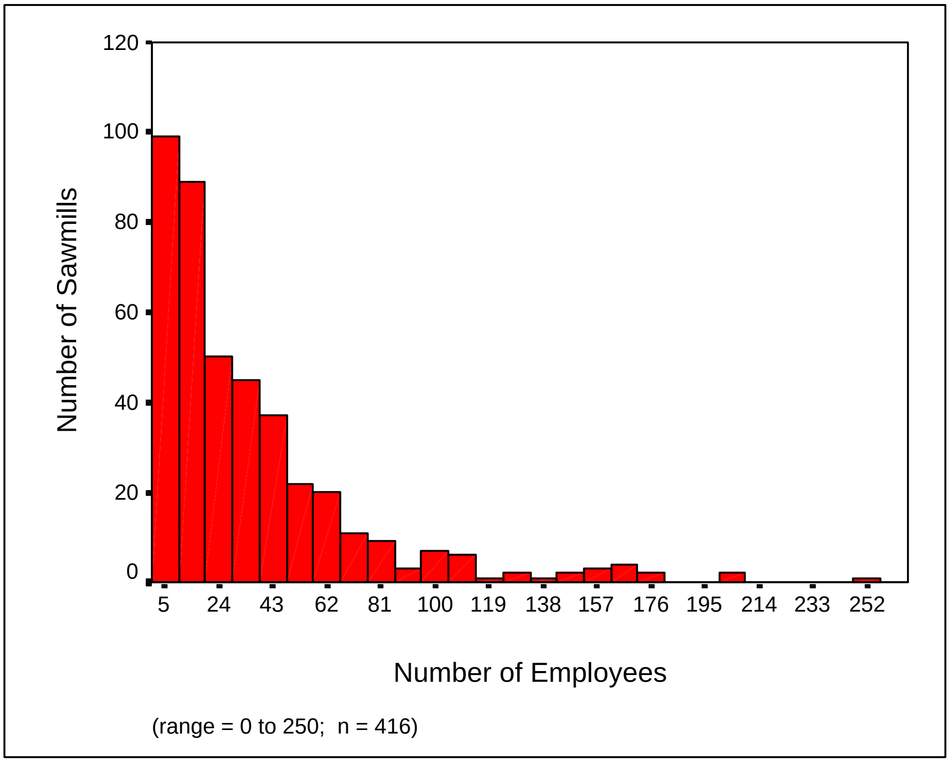

Figure 2-2: Distribution of Employee Numbers

As mentioned previously, employee numbers were used to define company size. Small companies were defined with 19 or fewer employees and large companies were defined with 20 or more employees. We examined company size by NHLA affiliation. Over 88 percent of the large companies were NHLA members and over 65 percent of the small companies were non-NHLA members (Table 2-2). This discrepancy in membership could represent two possibilities. The first is that the smaller companies produce and sell a product that does not utilize NHLA grading rules such as custom sawing, cants, or pallet stock. Second, it is possible that these smaller companies are unable to see the benefit of membership in trade associations or are unable to justify the cost.

Table 2-2: Company Sized Based on NHLA Affiliation

Affiliation	Small Company		Large Company	
	Frequency	Percentage	Frequency	Percentage
NHLA Member	66	34.4%	198	88.4%
Non-NHLA Member	126	65.6%	26	11.6%

Small Company = 19 or fewer employees (n = 192)
Large Company = 20 or more employees (n = 224)

Information on value adding capabilities was gathered. The respondents were able to select the types of value adding services that they offered. Examples of these processes included air drying, kiln drying, and surfacing (Table 2-3).

Table 2-3: Value Added Processes

Value Added Process	Frequency	Percentage
NHLA Grading	267	63.0%
End Coating	234	55.2%
Air Drying	218	51.4%
Kiln Drying	184	43.4%
Custom Sorting	167	39.4%
Surfacing	148	34.9%
Custom Grading	135	31.8%
Dimension Manufacturing	103	24.3%
Other	49	11.6%
(n = 424)		

NHLA Grading and *End Coating* were the two most common value added processes among the respondents at 63 percent and 55 percent respectively. This question provided a validity check. Sixty-three percent of the overall respondents were NHLA members which corresponds with those selecting the NHLA value added category. Forty-nine responding companies also listed other value added processes. Common examples of these included *custom sawing & sizing*, *pallet manufacturing*, *flooring manufacturing*, and *cabinet & furniture manufacturing*.

Existing sawmill technology may influence a company's decision to purchase other sawmill technology. Information on the current state of respondent's sawmill technology was collected (Table 2-4).

Table 2-4: Existing Sawmill Technology

Existing Technology	Frequency	Percentage
Bucking-optimizer	2	0.5%
Headrig-optimizer	115	27.1%
Edger-optimizer	43	10.1%
Grade Mark Reader	18	4.2%
Trimmer-optimizer	19	4.5%
Automated Sorting	30	7.1%
Other	21	5.0%
(n = 395)		

Headrig optimization was by far the most frequent existing technology in use by 27 percent of the responding companies. The next most prevalent technology were edger-optimizers which were in use by 10 percent of the respondents. Less than 5 percent of the respondents had trimmer-optimizer systems. The most frequent examples of *other* technologies listed by the respondents included specific brands of the technologies listed in Table 2-4. Further examples of *other* technologies included *lasers*, *optimizing chopsaws*, *optimizing ripsaws*, and most interestingly, *good people who care*.

Table 2-4 indicates that technology in hardwood sawmills is not that common. Even though carriage or headrig optimization is the most common technology in the hardwood sawmill, approximately 73 percent of hardwood sawmills still do not have this technology. Concerning scanning and optimizing technology such as edger-optimizers and trimmer-optimizers, approximately 90 percent and 95 percent (respectively) of companies do not have this technology. This indicates that hardwood sawmills remain a low technology industry segment.

Estimates on yearly hardwood lumber production were collected. This information will be useful in extrapolating hardwood lumber production nation wide. The mean lumber production for 1998 was 7,582,668 bdft. The median and mode were 5,000,000 bdft and 3,000,000 bdft respectively. A five percent trimmed mean was 6,700,995 bdft. Overall, production volumes differed greatly and ranged from 400 bdft to 54,000,000 bdft (Figure 2-3).

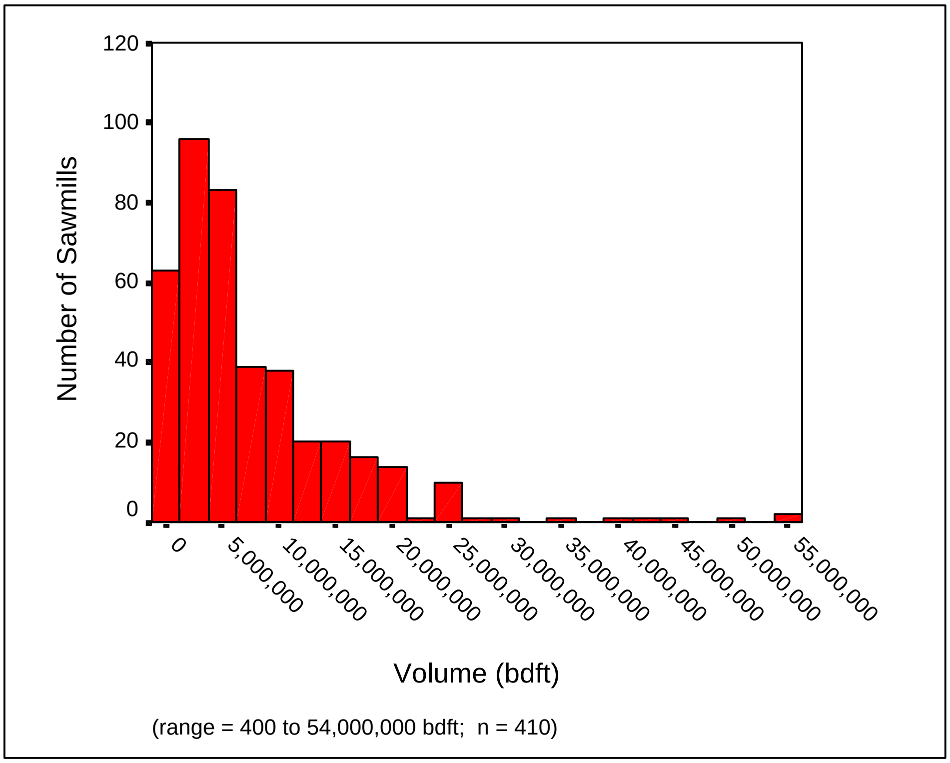

Figure 2-3: 1998 Hardwood Production Volumes

An examination of hardwood production volume by company size helps one visualize *small* and *large* companies. According to the definition of a small company having 19 or fewer employees, the mean production in 1998 was 2,573,906 bdft. Large companies with 20 or more employees generated a mean production of 11,674,753 bdft. On average, large companies produce 4.5 times more than small companies produce (Table 2-5).

Table 2-5: 1998 Production Volumes, Small vs. Large Companies (bdft)

Statistic	Small Company	Large Company
Mean	2,573,906	11,674,753
Median	2,500,000	10,000,000
Mode	3,000,000	10,000,000
5 % Trimmed Mean	2,284,516	10,690,416
Range	400 - 17,500,000	1,600,000 - 54,000,000
Small Company = 19 or fewer employees (n = 184) Large Company = 20 or more employees (n = 222)		

Hardwood production volumes can also be examined by organizational affiliation. Responding companies that were NHLA members had a mean production value of 10,262,284 bdft. In contrast non-NHLA member had a mean production value of only 2,806,940 bdft. Five percent trimmed means for NHLA members versus non-NHLA members were 9,300,377 bdft and 2,349,352 bdft respectively.

In addition to the total hardwood lumber volume data, specific data was collected on the species of tree processed by the responding sawmills. This in conjunction with the total hardwood lumber production in 1998 provides a clearer picture of the hardwood lumber market (Table 2-6). The frequency column shows the number of respondents that process a given species. At the top, red oak was processed by 357 of the responding companies. White oak and ash followed with 304 and 267 respondents respectively. The percentage column represents each species percentage of the total production volume of the responding companies. For example, 34.2 percent of the total hardwood volume reported in the questionnaire data was red oak.

Table 2-6: Lumber Breakdown by Species

Species	Frequency	Percentage of Total Volume
Red Oak	357	34.2%
Yellow-Poplar	240	16.0%
White Oak	304	15.5%
Hard Maple	237	8.8%
Soft Maple	252	5.9%
Black Cherry	216	4.7%
Ash	267	3.9%
Red Alder	2	2.0%
Aspen or Cottonwood	60	1.8%
Black Walnut	127	1.0%
Other Hardwoods	193	6.3%
Total		100%
(n = 362)		

To complement the 1998 hardwood lumber production data, the respondents were asked to provide their 1998 hardwood lumber sales. This information could also be useful in extrapolating hardwood lumber sales nation wide. The mean for lumber sales in 1998 was $5,627,343. The median and mode were $3,5000,000 and $3,000,000 respectively.

A 5 percent trimmed mean for the 1998 hardwood lumber sales was $4,809,185. This is almost $1 million less than an untrimmed mean. This is to be expected since several data points over $30,000,000 were not included in this trimmed calculation.

Paralleling the production volumes, sales values differed greatly and ranged from $160 to $43,000,000. Figure 2-4 illustrates the 1998 sales totals for the responding companies.

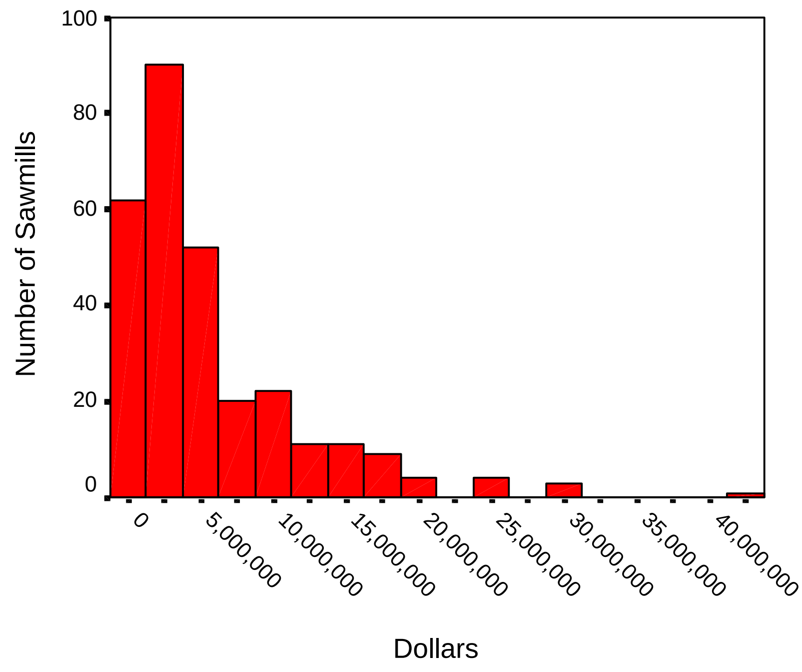

Figure 2-4: 1998 Hardwood Lumber Sales

An examination of the data by company size and NHLA affiliation was performed to parallel the production data. Consider company size. Mean hardwood lumber sales for large companies were over 5 times greater than for small companies. The maximum sales figure was 2.7 times greater for large companies versus small companies (Table 2-7).

Table 2-7: 1998 Hardwood Lumber Sales, Small vs. Large Companies

Statistic	Small Company	Large Company
Mean	$1,650,326	$8,640,492
Median	$1,259,000	$6,364,284
Mode	$2,000,000	$3,500,000
5 % Trimmed Mean	$1,425,221	$7,914,453
Range	$160 - $16,000,000	$330,000 - $43,000,000

Small Company = 19 or fewer employees (n = 127)
Large Company = 20 or more employees (n = 159)

In 1998, responding companies that were NHLA members had a mean sales value of $7,698,046. In contrast non-NHLA members had a mean sales value of only $1,647,579. Five percent trimmed means for NHLA members vs. non-NHLA members were $6,959,525 and $1,410,262 respectively.

The final company demographic examined production rates and work shifts. The purpose was to identify the speed of current hardwood sawmill production systems. Three hundred and fifty-five companies worked one shift while 61 worked two shifts. The mean shift length was 8.5 hours with a median and mode of 8.0 hours. Eight hour, 9 hour, and 10 hour work days represent the majority with 43, 22, 16 percent of the responses respectively (Figure 2-5).

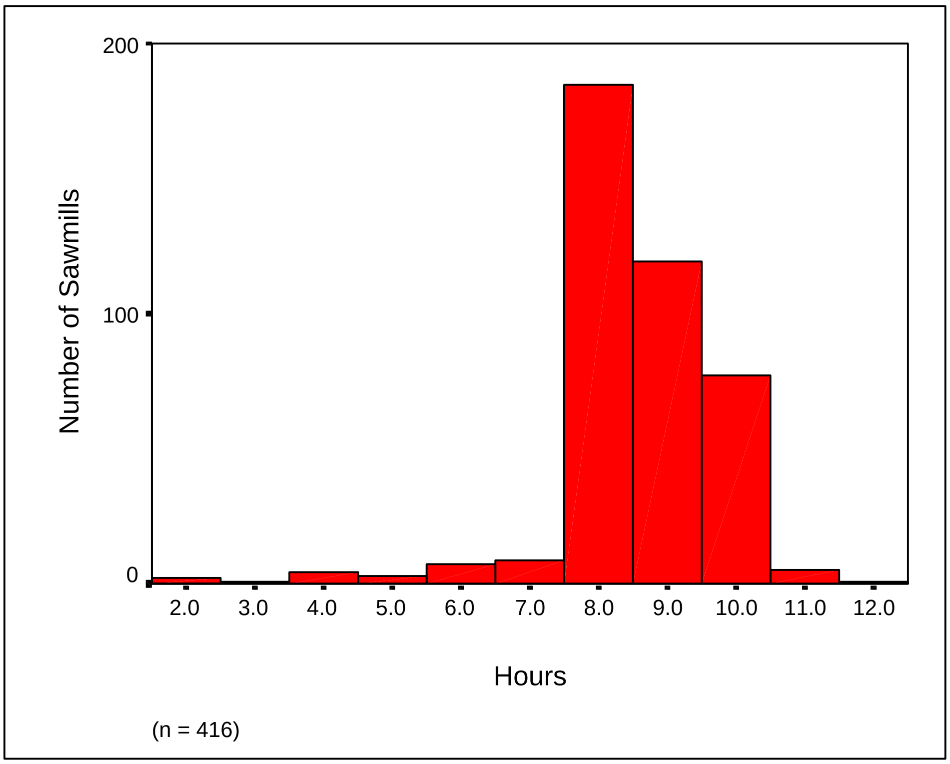

Figure 2-5: Average Shift Length

Hourly production rates were evenly distributed. The largest response category was *1001-2000 bdft per hour* accounting for 23 percent of the responses. Interestingly, 32 sawmills (7.8 percent) had production volumes that fell into the highest category, *greater than 7000 bdft per hour*. Not surprisingly, 31 of these companies were classified as *large companies* (one of the 32 companies chose not to reveal their company size) (Table 2-8).

Table 2-8: Hourly Production Rates

Hourly Production Volume	Frequency	Percentage
0 - 1000 bdft per hour	74	18.0%
1001 - 2000 bdft per hour	95	23.1%
2001 - 3000 bdft per hour	65	15.8%
3001 - 4000 bdft per hour	51	12.4%
4001 - 5000 bdft per hour	49	11.9%
5001 - 6000 bdft per hour	30	7.3%
6001 - 7000 bdft per hour	16	3.9%
Greater than 7000 bdft per hour	32	7.8%
(n = 406)		

With respect to the non-NHLA members, a considerable drop in the number of companies that produce more than 2000 bdft per hour can be noticed. NHLA members have a more even distribution, with a greater number of companies that operate at higher production rates (Figure 2-6).

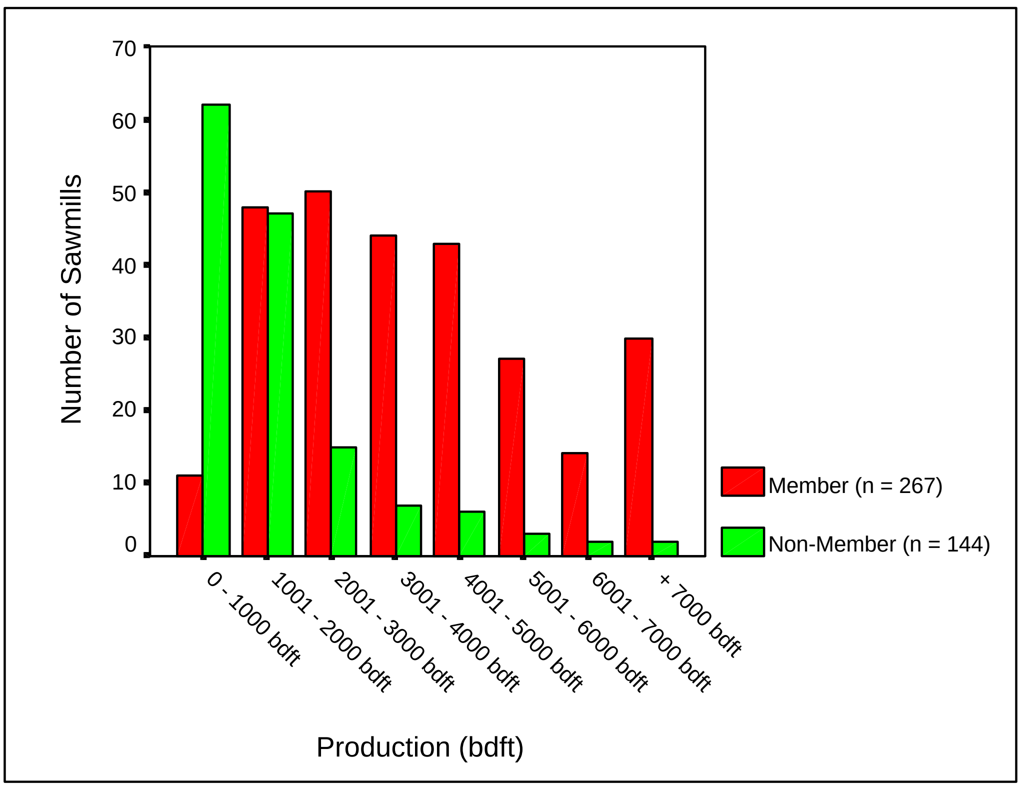

Figure 2-6: Hourly Production Rates for NHLA vs. Non-NHLA Members

Individual Respondent Demographics

Information on the individual that answers the questionnaire may lead to further insights. People of different backgrounds may perceive technology differently. This is especially important to this study. Information on the responding individual's position within the company, level of education, and age were examined.

Almost 70 percent of the respondents were owners and 25 percent responded as upper management personnel. Four companies marked the *other* category. These included positions such as *partner* or *sales personnel.* Table 2-9 summarizes their responses.

Table 2-9: Respondent's Position within the Sawmill

Sawmill Position	Frequency	Percentage
Owner	287	68.5%
Upper Management	107	25.5%
Middle Management	21	5.0%
Other	4	1.0%
(n = 419)		

Each questionnaire was targeted to the owner or upper manager. It was expected that the owner or mill manager would have the most pertinent information regarding technology in their mill. The middle management and other category may indicate that the questionnaire was passed down the chain of command.

Concerning education level, the largest responding group selected the *high school* category followed closely by the *four-year college* group. An additional 155 respondents had a college level education (Table 2-10). Fourteen respondents marked the *other* category. Typical responses included *NHLA Grading School*, *eighth grade*, *law school*, and *trade school*.

Table 2-10: Respondent's Level of Education

Level of Education	Frequency	Percentage
High School	149	35.6%
Two-year College	90	21.5%
Four-year College	126	30.1%
Graduate School	39	9.3%
Other	14	3.3%
(n = 418)		

The relationship between an individual respondent's level of education and the current level of technology in their sawmill was examined. Recall that this equipment included *bucking-optimizers*, *headrig-optimizers*, *edger-optimizers*, *trimmer-optimizers*, *grade mark readers*, and *automated sorting* (Appendix A). The data in Table 2-11 indicates that there is a relationship between educational levels and the use of technology.

Table 2-11: Level of Education based on Sawmill Technology

Level of Education	Has Technology		Does Not Have Technology	
	Frequency	Percentage	Frequency	Percentage
High School	40	26.1%	98	41.2%
Two-year College	33	21.6%	54	22.7%
Four-year College	54	35.3%	59	24.8%
Graduate School	22	14.4%	17	7.1%
Other	4	2.6%	10	4.2%
(Technology Companies n = 153; Non-technology Companies n = 238)				

Finally, age ranges were collected on the individual respondents. The largest response category was *40-49* with 41 percent responding followed by the *50-59* category with 25 percent responding (Table 2-12).

Table 2-12: Individual Respondent's Age Range

Age	Frequency	Percentage
Under 29	11	2.6%
30-39	74	17.6%
40-49	173	41.2%
50-59	106	25.2%
60 years and older	56	13.3%
(n = 420)		

The information gathered in the individual respondent profiles complement each other very well. The majority of the respondent's positions in the sawmill fell into the owner or upper management categories. This fit well with the higher age categories in which the majority of the respondents fell into.

Hardwood Sawmill System

Chapter 4 of this research explored the hardwood sawmill as a system. The model used broke the sawmill into four primary components including *raw material procurement*, *production process*, *sales & marketing*, and the *customer*. Several preliminary questions concerning this sawmill system were asked during the mail survey. A goal of this research was to understand if sawmills are managed as separate unrelated components or are managed as one interrelated entity.

Consider the previously mentioned sawmill model consisting of the four primary components (*raw material procurement*, *production process*, *sales & marketing*, and the *customer*). The questionnaire recipients were asked how important these components were when adopting new sawmill technology. The *production process* was rated the highest at 6.1 and was found to be significantly greater (alpha = 0.05) than the second highest rated component, *customer*, at 5.9. A significant difference was found between all component ratings except for *raw material procurement* and the *customer* (Figure 2-7).

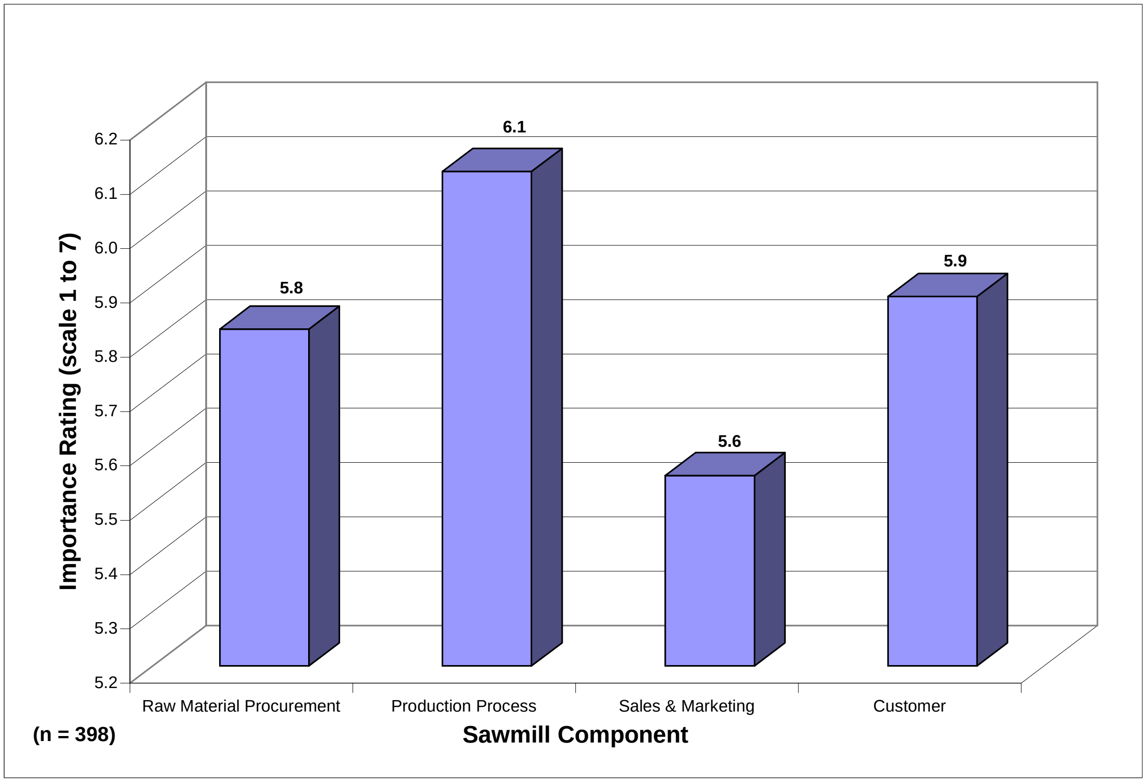

Figure 2-7: Importance Ratings for Sawmill Components

Comparisons by company size, company technology, and NHLA affiliation were made. In each case, the mean rating for *production process* was significantly higher (alpha = 0.05) for large companies, current technology companies, and NHLA members. Many industries consider the production of their product to be paramount. This is demonstrated to be true in hardwood sawmills by the significantly higher rating of *production process* (Table 2-13).

Table 2-13: Importance Ratings for Sawmill Components: Comparisons by Company Size, Company Technology, and NHLA Affiliation

Sawmill Component	Large Companies Mean Importance (n = 219)	Small Companies Mean Importance (n = 173)
Raw Material Procurement	5.9	5.7
Production Process	6.3	5.8*
Sales & Marketing	5.6	5.5
Customer	5.9	5.9
Sawmill Component	**Current Technology Mean Importance (n = 145)**	**No Technology Mean Importance (n = 227)**
Raw Material Procurement	5.9	5.8
Production Process	6.4	5.9*
Sales & Marketing	5.7	5.5
Customer	6.0	5.8
Sawmill Component	**NHLA Member Mean Importance (n = 261)**	**Non-NHLA Member Mean Importance (n = 136)**
Raw Material Procurement	5.9	5.6
Production Process	6.3	5.7*
Sales & Marketing	5.6	5.4
Customer	5.9	5.8

* Indicates significant difference between sawmill component ratings at alpha = 0.05

The study participants were asked if technology adoption decisions were individual decisions made by the senior decision-maker, or if the decisions were made by a group from across the sawmill. Forty-one percent (165) stated that it was an individual decision and 59 percent (241) stated that it was a group decision.

When asked if the sawmill had a mission statement 68.0 percent (268) responded *No* and 32.0 percent responded *Yes*. This may suggest that most hardwood sawmills have not been exposed to the principles of developing a company mission statement or have not seen the value of doing so.

Information Sources

When a sawmill considers adding equipment to its production facility, there are many places it can gather information. Hardwood lumber scanning and optimizing technology such as headrig scanners, edger-optimizers, and bin sorters are common examples of this equipment. Several questions were asked to collect data on the value of different information sources.

The information sources *plant visits* and *peer conversations* were rated the highest at 5.3. *Unsolicited sales literature* rated near the bottom, as did *university extension personnel.*

Finally, the *Internet* rated last at 3.0 out of 7.0. This finding is contrary to current trends in training and education, but the findings are similar to other research in the wood products industry (Bowe *et al.* 1999) (Table 2-14).

Table 2-14: Information Source Ratings

Factor	Mean Rating	Subsets (alpha = 0.05)					
Plant Visits	5.3	*					
Peer Conversations	5.3	*					
Association Meetings	4.3		*				
Personal Sales Calls from Manufacturers	4.1		*	*			
Meetings & Symposiums	4.0		*	*	*		
Short Courses	3.9			*	*		
Trade Journals	3.9			*	*		
Consultants	3.8			*	*	*	
Manufacturer's Ads & Literature	3.8			*	*	*	
News Letters	3.7				*	*	
Scientific Journals	3.7				*	*	
University Extension Personnel	3.6				*	*	
Unsolicited Sales Literature	3.5					*	
Other	3.4						*
Internet	3.0						*

* Asterisks indicate significantly different group means at an alpha level of 0.05 using Tukey's Honestly Significant Difference test for homogeneous subsets.
(n = 366)

An important question to ask is if the differences in these ratings are significant. Analysis of variance (ANOVA) found that there were significant differences between factor ratings (alpha = 0.05). One method to identify which factors rate similarly and differently is the Tukey's Honestly Significant Difference test (HSD). Tukey's HSD groups like means together. Table 2-14 shows the factors that demonstrated like means according to Tukey's HSD (alpha = 0.05). Asterisks grouped by column show the factors where the differences were not significant. It must be noted that at alpha = 0.05, Type 1 error may result within the 15 factor ratings.

Plant visits and *peer conversations* were found to be significantly different than the other groups. The *Internet* was found in the bottom significantly different group. The *other* category contained 18 responses. The main themes recorded in the open-ended portion of this question included *watch it in operation*, *talk to owners of installed equipment*, *verified results from operations*, and *see it at trade shows*.

Following the previous comparison procedures, these information sources were compared between large and small companies. Significant differences were found between five information source ratings (Independent Sample T Test, alpha = 0.05). *Plant visits*, *peer conversations*, *association meetings*, *personal sales calls from manufacturers*, and *meetings and symposiums* were all rated significantly higher by large companies (Table 2-15). All five of these information sources involve one-on-one interaction and were rated as the five highest information sources

Table 2-15: Information Source Ratings: Large vs. Small Companies

Information Sources	All Companies Mean Rating	Large Companies Mean Rating	Small Companies Mean Rating
Plant Visits	5.3	5.7	4.8*
Peer Conversations	5.3	5.5	5.0*
Association Meetings	4.3	4.5	4.1*
Personal Sales Calls from Manufacturers	4.1	4.2	3.9*
Meetings & Symposiums	4.0	4.2	3.7*
Trade Journals	3.9	3.9	3.8
Short Courses	3.9	3.9	3.9
Manufacturer's Ads & Literature	3.8	3.9	3.7
News Letters	3.7	3.8	3.6
Scientific Journals	3.7	3.8	3.6
Consultants	3.8	3.7	3.9
University Extension Personnel	3.6	3.7	3.6
Unsolicited Sales Literature	3.5	3.5	3.4
Other	3.4	3.2	3.5
Internet	3.0	3.1	2.9

* Indicates significant difference between information source ratings, independent sample t-test at alpha = 0.05
All Companies: n = 366; Large Companies: n = 156; Small Companies: n = 205

Comparison by company technology resulted in four significant differences in information source ratings. *Plant visits*, *association meetings*, *personal sales call from manufacturers*, and *meetings and symposiums* parallel the comparisons by company size (Table 2-16).

Table 2-16: Information Source Ratings: Technology vs. Non-technology Companies

Information Sources	All Companies Mean Rating	Current Technology Mean Rating	No Technology Mean Rating
Plant Visits	5.3	5.8	5.0*
Peer Conversations	5.3	5.5	5.2*
Association Meetings	4.3	4.6	4.1*
Personal Sales Calls from Manufacturers	4.1	4.4	3.8*
Meetings & Symposiums	4.0	4.2	3.8*
Trade Journals	3.9	4.0	3.7
Short Courses	3.9	3.9	3.9
Manufacturer's Ads & Literature	3.8	3.9	3.7
Scientific Journals	3.7	3.8	3.6
Consultants	3.8	3.8	3.9
News Letters	3.7	3.8	3.7
University Extension Personnel	3.6	3.6	3.6
Unsolicited Sales Literature	3.5	3.6	3.4
Other	3.4	3.2	3.4
Internet	3.0	3.1	2.9

* Indicates significant difference between information source ratings, independent sample t-test at alpha = 0.05
All Companies: n = 366; Technology Companies: n = 138; No Technology Companies: n = 205

NHLA and non-NHLA members were compared. Nine significant differences were found between the groups. NHLA member ratings were higher than non-NHLA member ratings in all nine cases (Table 2-17). These differences closely paralleled the comparisons by company size and company technology. The information sources that were significantly different centered on personal interaction.

Four information sources that were not found significantly different in the other group comparisons were *short courses, trade journals, newsletters,* and *scientific journals*. Short courses offer the before mentioned personal interaction and are regularly organized by the NHLA. The other three information sources do not offer personal interaction. It is possible that the NHLA is very effective in using print media and their members react to this media positively.

Table 2-17: Information Source Ratings: NHLA Members vs. Non-NHLA Members

Information Sources	All Companies Mean Rating	NHLA Member Mean Rating	Non-NHLA Member Mean Rating
Plant Visits	5.3	5.6	4.7*
Peer Conversations	5.3	5.5	5.0*
Association Meetings	4.3	4.6	3.8*
Personal Sales Calls from Manufacturers	4.1	4.2	3.7*
Meetings & Symposiums	4.0	4.2	3.4*
Short Courses	3.9	4.0	3.6*
Trade Journals	3.9	4.0	3.6*
Consultants	3.8	3.9	3.7
Manufacturer’s Ads & Literature	3.8	3.9	3.6
News Letters	3.7	3.8	3.4*
Scientific Journals	3.7	3.8	3.4*
University Extension Personnel	3.6	3.7	3.4
Unsolicited Sales Literature	3.5	3.5	3.4
Other	3.4	3.5	3.2
Internet	3.0	3.1	2.9

* Indicates significant difference between information source ratings, independent sample t-test at alpha = 0.05
All Companies: n = 366; NHLA Members: n = 247; Non-NHLA Members: n = 115

Another mechanism for gaining and sharing knowledge is through trade associations or professional associations. The sawmills that were sampled were asked to list the associations that they were members of. Over 140 different associations were listed. Table 2-18 shows the top 10 associations and their frequency. Not surprisingly, the NHLA was listed most frequently with 236 listings. This was expected since the NHLA membership list was used as part of the sample frame. The Hardwood Manufacturers Association followed the NHLA with 107 listings. Regional associations in the Lake States, Indiana, Virginia, Kentucky, West Virginia, and Pennsylvania demonstrate their importance and influence with high frequencies.

Table 2-18: Top 10 Associations by Membership Frequency

Trade Association	Frequency
National Hardwood Lumber Association	236
Hardwood Manufacturers Association	107
Lake States Lumber Association	23
Indiana Hardwood Lumbermens Association	22
Southern Lumber Manufacturers Association	22
Virginia Forest Products Association	19
Kentucky Forest Industry Association	18
West Virginia Forestry Association	18
Hardwood Lumber Manufacturers Association of Pennsylvania	15

Trade associations or professional association business meetings are additional sources of information and interaction between companies. The study participants were asked how many association meetings they attend annually. The average number of meetings was 3.0. The median and mode were 2 and 0 respectively.

Conclusions

This study sought to develop a national profile of the hardwood sawmill industry. This was achieved by compiling information on hardwood sawmill demographics, the hardwood sawmill as a system, and hardwood sawmill information sources. Several interesting, if not surprising results deserve reiteration.

Company size based on the number of employees is larger than one might expect based on the notion of small family run businesses. A five percent trimmed mean of 29.5 employees suggests that a typical hardwood sawmill would fall into our classification of a large company.

Hardwood sawmills affiliated with the NHLA demonstrated several positive characteristics when compared to non-NHLA members. Over 88 percent of large companies are NHLA members while over 65 percent of small companies are non-NHLA members. On average, the NHLA members produced almost 7 million bdft per year more than non-NHLA members. This trend is paralleled in the production rate data with the majority of the NHLA members producing in the top seven production categories. The majority of the non-NHLA members produced in the bottom two production categories. Overall, comparisons showed that large companies, NHLA members, and technology companies were similar and outperformed their counterparts.

Individual respondent demographics were also examined. Over 60 percent of the respondents had at least two years of college.

Existing sawmill scanning and optimizing equipment was examined. Despite a common belief that the hardwood sawmill industry is rapidly adopting new technologies, the majority of the hardwood sawmills have not. Headrig optimization, one of the oldest and broad technologies was most common and used by 27 percent of the respondents. Newer technologies such as edger-optimizers and trimmer-optimizers were in use by approximately 10 percent and 5 percent of the respondents respectively. From this data, 73 percent of all sawmills have no type of scanning or optimizing equipment in their sawmill.

The hardwood sawmill was modeled as a system by dividing it into four distinct departments. The *production process* was rated the highest. When examining the same model by comparing large versus small companies, NHLA versus non-NHLA members, and technology versus non-technology companies, *production process* was found to be significantly higher for large, NHLA, and technology companies (alpha = 0.05). This was contrary to initial expectations. Initially, it was thought that companies such as those with technology would be more progressive in viewing the sawmill as a system by rating the different sawmill components more evenly.

Information sources were examined. Personal interaction such as *plant visits* and *peer conversations* were rated at the top. These were information sources that involved direct personal interaction. The *Internet* was rated at the bottom. This was true for all comparison groups and is supported by earlier wood products industry research. For the hardwood sawmill industry, the Internet is not seen as an effective information tool.

The two most cited trade associations were the NHLA and the Hardwood Manufacturers Association. Given the industries' preference for personal interaction, association forums would be well suited for research and outreach activities.

The results of this study show that production issues are considered important in hardwood sawmills. Equipment such as scanning and optimizing technology are specifically designed to improve the production process and raw material utilization. For the future productivity of the hardwood sawmill industry, it is important that we understand what the sawmills expect from this technology. Understanding these expectations and decision-making process will benefit the hardwood sawmills, equipment manufacturers, and our renewable hardwood natural resources.

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CHAPTER 3: Market Segment Analysis of Advanced Scanning and Optimizing Technology in the Hardwood Sawmill Industry

Introduction

In the previous chapter, we examined the nature of the hardwood sawmill. Data was compiled to develop a current understanding of the industry as a whole. The importance of this industry was demonstrated by the yearly consumption of over 13 billion bdft of hardwood lumber in the U.S. (Hansen & West 1998). This material is the foundation of many value-adding industries worth tens of billions of dollars (U.S. Census Bureau 1999).

Other segments of the forest products industry have seen significant technological leaps. Engineered wood products have developed new production technologies, adapted to underutilized as well as a changing raw material base. These new technologies and new products are instrumental in meeting the increasing demand for wood products.

The hardwood lumber industry has not followed this trend, however. The previous chapter showed that the hardwood sawmill industry, as a whole, is not technologically advanced. Nearly 73 percent of hardwood sawmills do not have any type of scanning or optimizing technology. Only 10 percent have advanced scanning and optimizing technology such as an edger-optimizer. Technologically, there is a great deal of room for improvement in the hardwood sawmill industry.

The demographics of the hardwood sawmill industry may in part drive this reluctance to adopt new technology. Despite the recent trend toward consolidation in the hardwood sawmill industry, a significant portion of the sawmills are small. Companies of this nature may not have the capital or the supporting market share to justify purchasing advanced technology equipment. Estimates from the *Weekly Hardwood Review* suggest that the 50 largest sawmills only represent 15 percent of the total hardwood production with no single company producing more than 1.5 percent (Cited in Kincaid, 1998). A significant number of large and medium sized mills do exist, however, and are a potential market for hardwood sawmill technology.

The existence of several manufacturers of commercial scanning and optimizing technology suggests that there is a market for this equipment; however, this market is not well developed. A small segment of hardwood sawmills have adopted advanced scanning and optimizing technology such as edger-optimizers and trimmer-optimizers. As the names suggest, these technologies are designed to optimize (or partially optimize) production. From an environmental perspective, scanning and optimizing technology is designed to utilize the raw material more efficiently. From a business perspective, scanning and optimizing technology is designed to produce higher grade yield, quality, and consistency which leads to higher profit margins for the sawmill.

Hardwood sawmill demographics may be one reason for the slow adoption of this technology. Slow diffusion may also stem from the lack of quality market information supporting scanning and optimizing technology. It is necessary to understand the factors that will lead hardwood sawmills to adopt this technology.

The *newness* of scanning and optimizing technology is a combination of adapting it from the softwood industry to the needs of the hardwood industry and engineering the scanning ability to much higher levels. Here several problems arise because the sawmill customer is not understood. First, the differences between those companies that adopt this technology and those companies that do not adopt are unknown. From a marketing perspective, these differences need to be identified to better define the market. Second, several manufacturers produce scanning and optimizing equipment yielding similar yet different benefits. The hardwood sawmill industries' expectations from this technology must be understood. Third, the hardwood sawmill industries' expectations of the next generation of technology must be understood.

This information will provide scientists and developers of this technology with needed information to assist in the development and adoption of scanning and optimizing technology. Ultimately, adoption of this technology will provide better production yields and moderate the demand on our hardwood forests.

Objectives

The objectives of this chapter were:

1. Determine the differences between company characteristics for both adopter and non-adopters of hardwood lumber scanning and optimizing technology.

2. Identify company expectations of hardwood lumber scanning and optimizing technology: cost and feature levels of hardwood lumber scanning and optimizing technology systems that will be accepted by the hardwood lumber industry.

Methodology

Population

The population of interest was hardwood sawmills in the United States. Given the nature of the hardwood forest resource in the United States, the majority of the sawmills sampled were East of the Mississippi River; however, it was not limited to this region.

Subsets of the hardwood sawmill population such as Amish sawmills and micro-mills would not likely represent a significant (if any) portion of the hardwood sawmills interested in or suitable for hardwood lumber scanning and optimizing technology (micro-mills refer to the large number of small portable and band mills popular as hobbies or side businesses).

Sample Frame

Two recently compiled hardwood sawmill mailing lists were acquired. These included the National Hardwood Lumber Association's (NHLA) membership list and a non-NHLA member hardwood sawmill survey list. Since there may be inherent bias in any trade association membership list, it was important to incorporate this second group.

The first mailing list was made up of the NHLA's 1999 members which represented 1200 hardwood companies. Of the 1200 NHLA members, approximately 602 companies represented actual hardwood sawmills. It was expected that the demographics of NHLA members would be conducive to hardwood lumber scanning and optimizing technology; therefore, all 602 companies were included.

The second mailing list was originally generated for a 1998 hardwood sawmill study by the NHLA. The NHLA wanted to determine why various hardwood sawmills were not members. Using Standard Industrial Classification codes and state wood manufacturing directories, the NHLA in conjunction with the USDA Northeastern Forest Research Station, generated a list of 3600 non-NHLA member hardwood sawmills across the United States. Since many of these companies were small producers, they may be less likely to consider hardwood lumber scanning and optimizing technology. Therefore, a random sample of 1440 companies was selected. This sample kept the overall mail survey manageable and still provided statistical validity in comparison.

Fortunately, the recent survey performed by the NHLA provided suitable parameters and standard deviations to base this studies sample size on. Hardwood lumber production was a fitting parameter to use. This parameter was identified in the NHLA member database. The NHLA member hardwood lumber board foot (bdft) production standard deviation was 5,693,514 board feet. To achieve a confidence interval with a 90 percent confidence level and a precision of 6 percent (as a percentage of the mean bdft production, 500,000 bdft), the minimum study sample size was 351. Based on a comparison with a recent Virginia sawmill survey (production and employee parameters), this sample size was conservative (Alderman *et al.* 1999).

A typical response rate for a sawmill survey is less than 30 percent; therefore, all 602 NHLA member sawmills and 1440 non-NHLA member sawmills were targeted to achieve the desired response. This conservative sample size was expected to raise the confidence and precision levels above the acceptable base.

Data Collection

The mail survey followed the Total Design Method (Salant & Dillman 1994). This involved four mailings. The first mailing (sent in a 10X13 inch envelope) included a cover letter and a questionnaire form. It was mailed first class in September of 1999. The cover letter explained the nature and importance of the survey. It also stressed company anonymity of any information provided. The enclosed questionnaire utilized business reply postage for no cost return mailing for the sawmill. Approximately two weeks after the first mailing, a second mailing, which consisted of a follow-up post card, was sent. The post card thanked the sawmills for their response or urged them to reply if they had not. In October, two weeks after the second mailing, a third mailing was sent first class to those companies that had not responded. The third mailing (sent in a 10X13 inch envelope) included a revised cover letter and a second copy of the questionnaire form. Finally, a fourth mailing consisting of a reminder post card followed one week after the third mailing (Appendix A).

Concerning questionnaire content, the questions were designed to gather timely information on advanced scanning and optimizing technology in the hardwood sawmill. Specifically, these questions examined current edger-optimizers based on wane only information; future edger-optimizers based on NHLA grading rule information (full defect information); and future automated grading systems based on full defect information. These questions used a seven point Likert scale. These scale questions consisted of an array of factors related to scanning and optimizing technology. The respondents rated each factor with 1 representing *least important* and 7 representing *most important*. These three sections were the basis of the questionnaire and provided a base for the technology adoption model. In addition, several open-ended questions were incorporated to give the respondents an opportunity to expand on their ideas. The questionnaire, cover letters, and post card are shown in Appendix A.

The questions were also designed to address specific research objectives. Experts from Virginia Tech and the U.S. Forest Service Southern Research Station assisted in the questionnaire development.

International experience was also incorporated into the questionnaire design. The principle investigator had the opportunity to attend the Ligna World Fair for the forestry and wood industries in Hannover, Germany in May of 1999. This trade show provided the opportunity to design and discuss specific technology based questions with all hardwood lumber scanning and optimizing technology manufacturers worldwide. In addition, several hardwood sawmills were visited in Northern Germany. Here the researcher was able to see the technology in German hardwood sawmills and interact with their management teams.

Question types and formats were pre-tested in March at the 1999 Hardwood Lumber Manufacturers trade show in Charleston, North Carolina. During the summer of 1999, the completed survey was faxed to ten hardwood sawmills for final pre-testing. Eight companies responded to the faxes after consistent prodding. Only minor formatting issues were identified and changed during the pre-testing phase.

Data Analysis

The returned questionnaires were examined for completeness and usability. Useable surveys were coded and entered into an SPSS® Statistical Data Analysis package computer spreadsheet. SPSS is designed for survey analysis and readily provides summary statistics and comparison statistics for the various survey responses.

Under the topic of scaling, there is often debate on whether means can be calculated from nominal survey data. The common Likert scale is such an example. In this study, however, it was assumed that the Likert scale was equivalent between nominal data points (thereby representing interval data). Means could then be generated for these data which allowed for analysis with conventional based statistics.

To understand the differences and similarities between groups, comparisons were generated from the questionnaire data. The primary comparisons were made between three group types. These included company size, trade association affiliation, and existing installed technology.

Employee numbers were used to define company size. Two general categories, *small companies* and *large companies*, were defined. Companies with 19 or fewer employees were considered small while companies with 20 or more employees were considered large. This breakdown was consistent with other research in the wood products industry (Hansen & Smith 1997).

The second comparison group used trade association affiliation. The NHLA was chosen for two reasons. First, the NHLA has historically and currently set the standards and certified hardwood lumber grades. In addition, the NHLA is the largest trade association for hardwood sawmills. Second, our mailing database was segregated by NHLA members and non-NHLA members which made for logical comparisons.

Finally, the third comparison group separated the responding companies by adopters and non-adopters of **current** installed scanning and optimizing technology. This equipment included *bucking-optimizers*, *headrig-optimizers*, *edger-optimizers*, *trimmer-optimizers*, *grade mark readers*, and *automated sorting* (Appendix A).

Results and Discussion

Response

Questionnaires were mailed to 2,042 companies. From these, 212 were returned undeliverable. Undeliverable included companies that have gone out of business or companies that moved without a forwarding address or had an expired forwarding address. Nineteen companies requested by phone or by letter to be removed from the study. This group included companies that were never or were no longer in the hardwood sawmill business. It also included companies that did not wish to participate in the study. One final company was determined to be a duplicate between the two mailing lists. Subtracting these companies from the total number left 1,810 companies as potential respondents.

In total, 600 questionnaires were returned. The first question asked the respondent if their company was a hardwood sawmill. One hundred and seventy answered *No*, while *Yes* was checked by 431 respondents. Seven of the surveys marked *Yes* were deemed unusable due to incompleteness. This brought the total useable level to 424 questionnaires. Our target number of useable surveys was 351. The total adjusted response rate was 23.5 percent (Table 3-1). The adjusted response rate was calculated by subtracting the bad addresses from the total mailing and dividing it into the usable responses.

Table 3-1: Mail Survey Response Figures

	Total	NHLA List	Non-NHLA List
Total Mailed	2,042	602	1,440
Bad Addresses	212	1	211
Removal Request	19	2	17
Returned	600	285	315
Hardwood Sawmill	431	272	159
Unusable	7	1	6
Useable	424	271	153
Total Adjusted Response Rate = 23.5%			
Adjusted Response Rate NHLA Mailing List = 45.3%			
Adjusted Response Rate Non-NHLA Mailing List = 12.7%			

Non-response Bias

Non-responding companies were randomly selected, contacted by phone, and asked five questions as they were printed on the questionnaire. A total of 30 calls were completed. Given the small sample size of this bias check, nonparametric statistical methods were used to check for statistical differences between the survey respondents and non-respondents. No significant differences were found between the respondents and non-respondents (Mann-Whitney test, alpha = 0.05).

Hardwood Sawmill Technology

The study had three primary sections on hardwood sawmill technology. Each individual section sought information on cost and features that are important when deciding to install a given technology. The sections were arranged in a chronological order with the first section examining current edger-optimizer systems. Current edger-optimizers partially optimize based on wane and size information only. The second section sought information on future edger-optimizer systems that are currently being developed. Future edger-optimizers fully optimize based on full defect information. Finally, the third section looked at future automated lumber grading systems. These systems grade based on full defect information.

Participants were asked if they believe that scanning and optimizing technology would benefit their sawmill. Twenty-seven percent (109) indicated *No* and 73 percent (290) indicated *Yes*. This suggests that most companies believe that technology will help them.

The respondents were asked to expand on their Yes/No answers with additional comments. By far, the largest response dealt with the ability of scanning and optimizing technology to improve recovery, yield, consistency, and speed. Sixty-three companies responded with this answer. The second most popular theme dealt with a negative perception of scanning and optimizing technology. Forty-seven respondents stated that the initial cost was too great, and that their company was too small to incorporate this technology. About 14 companies questioned the cost effectiveness of the technology stating that it may not pay for itself. Ten respondents specifically stated a benefit of scanning and optimizing technology is the removal of human error. Conversely, one respondent stated that he would not want to remove the human factor. This statement was supported by several other respondents claiming that the technology has not yet been proven or that they are not certain, but that they are looking into the technology. Fourteen other respondents stated that scanning and optimizing technology would not fit into their mill or that it would be of little value since they do not cut grade lumber. Finally, 8 respondents said that an automated hardwood lumber grading system would benefit their mill and the industry as a whole. One common misconception of scanning and optimizing technology is that it will save labor. Several companies stated this as a benefit when it may not be a reality.

Respondents were also asked if they believe that there is truthful and accurate information available on scanning and optimizing technology, 74.2 percent (267) responded *Yes* and 25.8 percent (93) responded *No*.

Current Edger-optimizer Systems

The respondents were asked to rate factors important in edger-optimizer adoption. Two factors, *improved raw material recovery* and *increased lumber revenues*, tied with the highest rating. The high rating of these two factors demonstrates the importance of profit margins in the hardwood sawmill industry. To promote the adoption of this technology, manufacturers should focus their attention on these factors. *Advice from customers* and *advice from sales department* rated at the very bottom. In general, production related factors were rated higher while non-production related factors were rated lower (Table 3-2).

Table 3-2: Factor Importance for Current Edger-optimizer Systems

Factor	Rank	Mean Importance	Subsets (alpha = 0.05)						
Improved Raw Material Recovery	1	6.5	*						
Increased Lumber Revenues	2	6.5	*						
System Lifespan	3	6.0		*					
Improved Lumber Quality	4	5.9		*					
Ability to Upgrade	5	5.9		*					
Availability of Vendor Support	6	5.8		*					
Increased Production Levels	7	5.8		*					
Improved Lumber Consistency	8	5.7		*					
Ease of Use	9	5.7		*					
Initial Cost	10	5.7		*					
Maintenance Costs	11	5.2			*				
Existing Mill Layout Restrictions	12	5.2			*				
Training from Vendor	13	5.1			*				
Operational Costs	14	5.1			*				
Installation Down Time	15	4.8			*	*			
Advice from Production Supervisors	16	4.7				*	*		
Training of New Operators	17	4.6				*	*		
Advice from Customers	18	4.4					*	*	
New Mill Installation	19	4.1						*	
Advice from Sales Department	20	3.7							*

* Asterisks indicate significantly different group means at an alpha level of 0.05 using Tukey's Honestly Significant Difference test for homogeneous subsets.
(n = 355)

An important question to ask is if the differences in these ratings are significant. Analysis of variance (ANOVA) found that there were significant differences between factor ratings (alpha = 0.05). One method to identify which factors rate similarly and differently is the Tukey's Honestly Significant Difference test (HSD). Tukey's HSD groups like means together. Table 3-2 shows the factors that demonstrated like means according to Tukey's HSD (alpha = 0.05). Asterisks grouped by column show the factors where the differences were not significant. It must be noted that at alpha = 0.05, Type 1 error may result within the 20 factor ratings.

One factor, *initial cost*, was expected to be rated highly but fell into the second group. This result may be explained in part from data in the open-ended questions. Initial cost may present a barrier for the smaller mills; however, potential payback and gain from the technology is a larger issue.

In addition to the factors that the respondents thought were important, information was collected on what they would be willing to pay for an edger-optimizer. It was clearly stated that the price included the scanners, computers, and edger but *not* the material handling system. Nearly 50 percent chose the lowest cost category, *less than $100,000*. Only one company chose the highest cost category of *greater than $1,000,000*. This particular company has several pieces of hardwood sawmill technology including a headrig-optimizer, a trimmer-optimizer, a grade mark reader, and an automated sorting system. Their annual production was 44.5 million board feet. This may help explain their selection of the highest price category (Table 3-3).

Table 3-3: Acceptable Cost for Current Edger-optimizers

Cost	Frequency	Percentage
Less than $100,000	179	49.4%
$100,001 - $250,000	94	26.0%
$250,001 - $500,000	56	15.5%
$500,001 - $1,000,000	32	8.8%
Greater than $1,000,000	1	0.3%
(n = 362)		

Three groups were examined to see if they rated current edger-optimizer factors differently. These groups were large versus small companies, technology versus non-technology companies, and NHLA members versus non-NHLA members.

Significant differences were found among 5 factors between small and large companies. Even though both large and small companies rated *improved raw material recovery* highly, large companies rated it significantly higher than small companies. This may indicate that with higher raw material costs and tighter profit margins, large companies consider the benefits of improved raw material recovery to be more critical than smaller companies (Table 3-4).

Table 3-4: Factor Ratings for Current Edger-optimizer Systems: Large vs. Small Companies

Factor	All Companies Mean Importance	Large Companies Mean Importance	Small Companies Mean Importance
Improved Raw Material Recovery	6.5	6.7	6.3*
Increased Lumber Revenues	6.5	6.6	6.3*
Availability of Vendor Support	5.8	6.0	5.6*
Ability to Upgrade	5.9	6.0	5.7
Improved Lumber Quality	5.9	5.9	5.9
System Lifespan	6.0	5.9	6.1
Increased Production Levels	5.8	5.8	5.8
Improved Lumber Consistency	5.7	5.7	5.8
Ease of Use	5.7	5.7	5.8
Initial Cost	5.7	5.6	5.8
Existing Mill Layout Restrictions	5.2	5.2	5.1
Training from Vendor	5.1	5.2	5.0
Maintenance Costs	5.2	5.2	5.3
Operational Costs	5.1	5.0	5.2
Installation Down Time	4.8	4.9	4.8
Advice from Production Supervisors	4.7	4.8	4.4*
Training of New Operators	4.6	4.4	4.8*
Advice from Customers	4.4	4.3	4.5
New Mill Installation	4.1	4.0	4.3
Advice from Sales Department	3.7	3.6	3.8

* Indicates significant difference between factor ratings, independent sample t-test at alpha = 0.05
Small Company = 19 or fewer employees (n = 152)
Large Company = 20 or more employees (n = 200)
All Companies (n = 355)

Large companies also rated *increased lumber revenues* significantly higher than small companies. This is despite the fact that *increased lumber revenues* was the highest rated factor by small companies. This may demonstrate more urgency by the large companies. Large companies rated *availability of vendor support* significantly higher than small companies. This may, in-part, be due to newer or more sophisticated equipment or a larger array of equipment in large hardwood sawmills.

Advice from production supervisors was rated higher by larger companies. A possible cause may be that large companies are more likely to have a production supervisor on staff, while small companies have one person, such as the owner or sawmill manager, play multiple roles within the sawmill. This would make it more difficult to distinguish between job descriptions.

Finally, *training of new operators* was rated significantly higher by small companies. On this issue, the large companies may feel that they have the expertise on staff to deal with the training and operation requirements of new technology.

Comparing companies that have technology to companies that do not have technology, three significant differences were identified. Recall that companies with technology were those that had systems such as *bucking-optimizers*, *headrig-optimizers*, *edger-optimizers*, *trimmer-optimizers*, *grade mark readers*, and *automated sorting*.

Both *improved raw material recovery* and *increased lumber revenues* were rated significantly higher by companies with technology as compared to companies without technology (Table 3-5). This is not surprising given that the companies with technology parallel the large companies, and the companies without technology parallel the small companies. Finally, companies without technology rated *initial cost* significantly higher. This is reasonable since initial cost could be the barrier preventing the adoption of technology by the small and non-technology companies.

Table 3-5: Factor Ratings for Current Edger-optimizer Systems: Technology vs. Non-Technology Companies

Factor	All Companies Mean Importance	Current Technology Mean Importance	No Technology Mean Importance
Improved Raw Material Recovery	6.5	6.6	6.4*
Increased Lumber Revenues	6.5	6.6	6.4*
Improved Lumber Quality	5.9	6.0	5.8
Availability of Vendor Support	5.8	6.0	5.8
Ability to Upgrade	5.9	6.0	5.8
System Lifespan	6.0	6.0	6.0
Increased Production Levels	5.8	5.7	5.9
Ease of Use	5.7	5.7	5.8
Improved Lumber Consistency	5.7	5.7	5.8
Initial Cost	5.7	5.5	5.8*
Training from Vendor	5.1	5.2	5.1
Maintenance Costs	5.2	5.2	5.3
Existing Mill Layout Restrictions	5.2	5.1	5.1
Operational Costs	5.1	5.0	5.2
Installation Down Time	4.8	4.9	4.8
Advice from Production Supervisors	4.7	4.9	4.6
Training of New Operators	4.6	4.5	4.6
Advice from Customers	4.4	4.2	4.5
New Mill Installation	4.1	4.1	4.2
Advice from Sales Department	3.7	3.5	3.8

* Indicates significant difference between factor ratings, independent sample t-test at alpha = 0.05
All Companies: n = 355; Current Technology: n = 127; No Technology: n = 208

Seven significant differences were found between the factor ratings of NHLA member and non-NHLA members. *Increased lumber revenues*, *improved raw material recovery*, and *availability of vendor support* were all rated significantly higher by NHLA members. This parallels the company size comparisons (Table 3-4). *Initial cost* and *training from vendor* were also rated significantly different. Non-NHLA members rated initial cost higher, which likely represents small companies where cost is a barrier.

Finally, *operational costs* and *advice from production supervisors* were rated significantly different between the groups. *Operational costs* was rated higher by non-NHLA members which likely represents small companies where cost is a significant barrier.

Table 3-6: Factor Ratings for Current Edger-optimizer Systems: NHLA Members vs. Non-NHLA Members

Factor	All Companies Mean Importance	NHLA Member Mean Importance	Non-NHLA Member Mean Importance
Increased Lumber Revenues	6.5	6.6	6.3*
Improved Raw Material Recovery	6.5	6.6	6.3*
Availability of Vendor Support	5.8	6.0	5.5*
System Lifespan	6.0	6.0	6.0
Improved Lumber Quality	5.9	6.0	5.9
Ability to Upgrade	5.9	5.9	5.8
Increased Production Levels	5.8	5.8	5.8
Improved Lumber Consistency	5.7	5.8	5.7
Ease of Use	5.7	5.7	5.8
Initial Cost	5.7	5.6	5.9*
Training from Vendor	5.1	5.3	4.8*
Existing Mill Layout Restrictions	5.2	5.2	5.1
Maintenance Costs	5.2	5.2	5.3
Operational Costs	5.1	5.0	5.4*
Advice from Production Supervisors	4.7	4.9	4.2*
Installation Down Time	4.8	4.9	4.8
Training of New Operators	4.6	4.5	4.7
Advice from Customers	4.4	4.4	4.5
New Mill Installation	4.1	4.1	4.2
Advice from Sales Department	3.7	3.6	3.8

* Indicates significant difference between factor ratings, independent sample t-test at alpha = 0.05
All Companies: n = 355; NHLA Members: n = 235; Non-NHLA Members: n = 119

Future Edger-optimizer Systems

Similar information was collected for future edger-optimizer systems as for the current edger-optimizer systems. Feature and cost data were collected. In addition, information was collected on the expected payback time for such technology.

The study participants were asked to consider future edger-optimizer systems based on NHLA grading rules (complete defect information). When asked what features or abilities these new systems would need to have, *improved raw material recovery* and *increased lumber revenues* were selected most frequently. It was surprising to see, however, that *training from vendor* was selected the least amount of times. This may be different with companies that have technology (Table 3-7).

Table 3-7: Feature Selection for Future Edger-optimizer Systems

Feature	Frequency	Percentage
Improved Raw Material Recovery	333	78.5%
Increased Lumber Revenues	327	77.1%
Reliability	321	75.7%
Initial Costs	284	67.0%
Ease of Use	280	66.0%
Product Consistency	255	60.1%
Flexible Grade Programming	251	59.2%
Availability of Vendor Support	246	58.0%
Maintenance Costs	244	57.5%
Increased Production Levels	230	54.2%
Training from Vendor	218	51.4%
(n = 424)		

There was a large separation between *increased lumber revenues* and *increased production levels*. Often these two terms are considered as one in the same. This clear separation in frequencies may imply that the respondents understand that board upgrade is a key goal for increased revenues. Increased production with no attention to board upgrade may not necessarily increase revenues.

Based on the features that respondents thought were important, information was collected on whether the respondent would consider installing a future edger-optimizer. Thirty-two percent said they would not be interested in installing such technology while 68 percent said they would consider installing the technology. When asked what they would be willing to pay for a future edger-optimizers, 37 percent chose the lowest cost category, *less than $100,000*. Again, it was clearly stated that the price included the scanners, computers, and edger but *not* the material handling system. Only one company chose the highest cost category of *greater than $1,000,000* (Table 3-8). Overall, respondents may be willing to pay more for future systems versus current systems. They may consider total defect information to be more valuable.

Table 3-8: Acceptable Cost for Future Edger-optimizers

Cost	Frequency	Percentage
Less than $100,000	106	37.6%
$100,001 - $250,000	83	29.4%
$250,001 - $500,000	62	22.0%
$500,001 - $1,000,000	30	10.6%
Greater than $1,000,000	1	0.4%
(n = 282)		

Finally, the respondents provided information on the expected payback, in years, for future edger-optimizer technology. The mean payback was 3.6 years. The median and mode of the payback were both 3.0 (Figure 3-1).

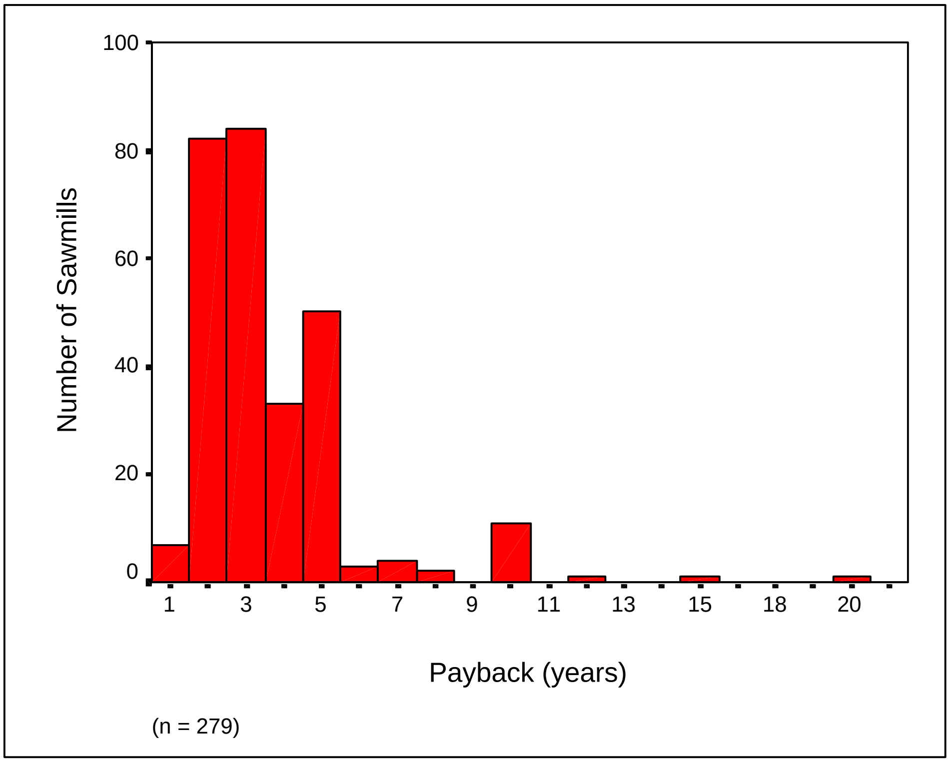

Figure 3-1: Expected Payback for Future Edger-optimizer Systems

It is clear that most companies think in 2, 3, 4, or 5 year payback periods. Only a few companies would consider payback periods greater than 5 years.

Future Automated Hardwood Lumber Grading Systems

As with current edger-optimizers and future edger-optimizers, we were interested in identifying the important factors and cost levels of automated grading systems. The respondent were asked to rate a number of factors that would be important for adopting future automated hardwood lumber grading systems. *Accuracy of Grading* was rated the highest by a large margin (Table 3-9). It was significantly different (alpha = 0.05) from the second rated factor *system lifespan*. This may demonstrate the hardwood sawmill industry's concern for such technology. The second and third rated factors, *system lifespan* and *durability*, demonstrate the importance of the durability of such an investment. *Color sorting capabilities* was rated last. As with the current edger-optimizer systems, *training from vendor* was rated near the bottom.

Table 3-9: Factor Ratings for Future Automated Hardwood Grading Systems

Factor	Rank	Mean Importance	Subsets (alpha = 0.05)						
Accuracy of Grading	1	6.6	*						
System Lifespan	2	5.9		*					
Durability	3	5.9		*	*				
NHLA Grading Rules	4	5.8		*	*	*			
Ability to Upgrade	5	5.8		*	*	*			
Initial Cost	6	5.8		*	*	*			
Reduction of Grading Costs	7	5.8		*	*	*	*		
Tallying Capabilities	8	5.8		*	*	*	*		
Simplicity of Operation	9	5.7		*	*	*	*		
Ease of Use	10	5.7		*	*	*	*		
Ability to Modify NHLA Grading Rules	11	5.7		*	*	*	*		
Availability of Vendor Support	12	5.6		*	*	*	*	*	
Speed	13	5.6			*	*	*	*	
Training from Vendor	14	5.5				*	*	*	
Ability to Quickly Switch Species	15	5.5				*	*	*	
Equipment Warranty	16	5.4					*	*	
Compatibility with Existing Equipment	17	5.4					*	*	
Sorting Capabilities	18	5.4					*	*	
Training of New Operators	19	5.3						*	
Color Sorting Capabilities	20	4.8							*

* Asterisks indicate significantly different group means at an alpha level of 0.05 using Tukey's Honestly Significant Difference test for homogeneous subsets.

(n = 359)

In addition to the factors that the respondents thought were important, information was collected on what they would be willing to pay for a future automated grading system. Again, it was clearly stated that the price included the scanners and computers but *not* the material handling system. Forty-eight percent chose the lowest cost category, *less than $100,000*. As with the current edger-optimizer systems question, this category may have been used as a default. Zero companies chose the highest cost category of *greater than $1,000,000*. Overall, these results were not much different than those from the current edger-optimizer or future edger-optimizer systems (Table 3-10).

Table 3-10: Acceptable Cost for Future Automated Hardwood Grading Systems

Cost	Frequency	Percentage
Less than $100,000	174	48.5%
$100,001 - $250,000	112	31.2%
$250,001 - $500,000	54	15.0%
$500,001 - $1,000,000	19	5.3%
Greater than $1,000,000	0	0.0%

(n = 359)

We examined differences in automated hardwood grading factor ratings by groups. These groups were organized by company size, company technology, and NHLA affiliation.

Significant differences were found between three factors including *speed*, *training from vendor*, and *initial cost* (Table 3-11). The rating for *speed* was significantly higher for large companies versus small companies. The high production rates of larger companies would require and automated grading system with speeds capable of handling high volumes and high feed rates.

Large companies also rated *training from vendor* significantly higher than small companies. This result was the exact opposite of the training issues rated under the current edger-optimizer question (Table 3-4). It is possible that these large companies felt comfortable with their current technical experience on existing technology but were uncertain about their expertise on future technology. It is also possible that smaller companies would not consider an automated hardwood grading system and saw no need for training. Finally, *initial cost* was rated significantly higher by small companies. Initial cost can be seen as a barrier to small companies.

Table 3-11: Factor Ratings for Future Automated Hardwood Grading Systems: Large vs. Small Companies

Factor	All Companies Mean Importance	Large Companies Mean Importance	Small Companies Mean Importance
Accuracy of Grading	6.6	6.7	6.5
Durability	5.9	6.0	5.8
System Lifespan	5.9	5.9	5.9
Ability to Upgrade	5.8	5.9	5.7
NHLA Grading Rules	5.8	5.9	5.7
Reduction of Grading Costs	5.8	5.9	5.6
Tallying Capabilities	5.8	5.8	5.7
Ability to Modify NHLA Grading Rules	5.0	5.8	5.6
Speed	5.7	5.8	5.3*
Availability of Vendor Support	5.6	5.7	5.4
Ease of Use	5.7	5.7	5.8
Simplicity of Operation	5.7	5.7	5.9
Training from Vendor	5.5	5.7	5.3*
Initial Cost	5.8	5.6	6.0*
Ability to Quickly Switch Species	5.5	5.5	5.5
Sorting Capabilities	5.4	5.5	5.4
Equipment Warranty	5.4	5.4	5.6
Compatibility with Existing Equipment	5.4	5.4	5.6
Training of New Operators	5.3	5.2	5.4
Color Sorting Capabilities	4.8	4.9	4.7

*** Indicates significant difference between factor ratings, independent sample t-test at alpha = 0.05**
Small Company = 19 or fewer employees (n = 147)
Large Company = 20 or more employees (n = 206)
All Companies (n = 359)

Company technology was also used as a basis for comparing automated hardwood lumber grading systems. Six significant differences were found between the two groups (Table 3-12). *Accuracy of grading* was rated the highest by both technology and non-technology companies. However, it was rated significantly higher by the technology group. This may represent existing experience with technology. The technology companies may understand that accuracy is key in successful optimization. Experience with technology may also explain why *ability to upgrade* was sated significantly higher by technology companies.

Speed, *availability of vendor support*, and *training from vendor* were all rated significantly higher by technology companies. Finally, *color sorting capabilities* was rated higher by technology companies. Many of the larger companies and companies with technology were vertically integrated. These companies often require color sorting and color matching capabilities.

Table 3-12: Factor Ratings for Future Automated Hardwood Grading Systems: Technology vs. Non-Technology Companies

Factor	All Companies Mean Importance	Current Technology Mean Importance	No Technology Mean Importance
Accuracy of Grading	6.6	6.8	6.5*
Ability to Upgrade	5.8	6.1	5.6*
System Lifespan	5.9	6.0	5.9
Durability	5.9	6.0	5.9
NHLA Grading Rules	5.8	6.0	5.8
Speed	5.6	5.9	5.4*
Ability to Modify NHLA Grading Rules	5.7	5.9	5.6
Reduction of Grading Costs	5.8	5.9	5.8
Availability of Vendor Support	5.6	5.9	5.4*
Tallying Capabilities	5.8	5.8	5.7
Ease of Use	5.7	5.7	5.7
Simplicity of Operation	5.7	5.7	5.8
Training from Vendor	5.5	5.7	5.4*
Initial Cost	5.8	5.7	5.9
Ability to Quickly Switch Species	5.5	5.6	5.5
Sorting Capabilities	5.4	5.5	5.4
Equipment Warranty	5.4	5.5	5.4
Compatibility with Existing Equipment	5.4	5.5	5.4
Training of New Operators	5.3	5.3	5.3
Color Sorting Capabilities	4.8	5.1	4.5*

* Indicates significant difference between factor ratings, independent sample t-test at alpha = 0.05
All Companies: n = 359; Current Technology: n = 135; No Technology: n = 197

The final comparison of future automated hardwood grading systems was by NHLA affiliation. Eight significant differences in factor ratings were found. As with the technology companies, *accuracy of grading* was significantly higher with NHLA members and was the highest rated factor (Table 3-13). Interestingly, *ability to modify NHLA grading rules* was rated at 5.9. It was not surprising that it rated higher than the non-NHLA members since they may not use the rules; however, it may indicate the NHLA members’ desire to modify the rules. This was further supported by several comments in the open-ended questions.

Tallying capabilities, *availability of vendor support*, *speed*, and *training from vendor* all were rated significantly higher by NHLA members. Finally, *initial cost* and *compatibility with existing equipment* were rated significantly higher by non-NHLA members. Again the non-NHLA members paralleled the smaller companies and initial cost is a significant barrier. Equipment compatibility can also be seen as a cost barrier based on modification expenses.

Table 3-13: Factor Ratings for Future Automated Hardwood Grading Systems: NHLA Members vs. Non-NHLA Members

Factor	All Companies Mean Importance	NHLA Member Mean Importance	Non-NHLA Member Mean Importance
Accuracy of Grading	6.6	6.7	6.4*
Durability	5.9	5.9	5.9
NHLA Grading Rules	5.8	5.9	5.7
System Lifespan	5.9	5.9	6.0
Tallying Capabilities	5.8	5.9	5.5*
Ability to Upgrade	5.8	5.9	5.7
Ability to Modify NHLA Grading Rules	5.7	5.9	5.5*
Reduction of Grading Costs	5.8	5.8	5.8
Availability of Vendor Support	5.6	5.8	5.3*
Simplicity of Operation	5.7	5.7	5.8
Ease of Use	5.7	5.7	5.8
Speed	5.6	5.7	5.4*
Training from Vendor	5.5	5.7	5.2*
Initial Cost	5.8	5.7	6.1*
Ability to Quickly Switch Species	5.5	5.6	5.5
Sorting Capabilities	5.4	5.5	5.3
Equipment Warranty	5.4	5.4	5.6
Training of New Operators	5.3	5.3	5.3
Compatibility with Existing Equipment	5.4	5.3	5.7*
Color Sorting Capabilities	4.8	4.9	4.6

* Indicates significant difference between factor ratings, independent sample t-test at alpha = 0.05
All Companies: n = 359; NHLA Members: n = 242; Non-NHLA Members: n = 114

Qualitative Responses

The respondents were given the opportunity to respond to several open-ended questions. When asked what negative things they have heard about hardwood lumber scanning and optimizing technology, the most common response was the high cost of technology which was listed most frequently at 94 times. Payback, mentioned 14 times, is closely related to cost. The second most frequent response listed 73 times was *none*. This could represent two possibilities: they really have not heard any negative comments in their discussions or they have not discussed this technology at all. Comments questioning the accuracy of this technology were listed 25 times. Reliability issues such as repairs and maintenance were listed 29 times. Related to these, downtime and complexity were other important issues listed 12 and 13 times respectively. One interesting theme is whether this technology performed as advertised or promoted. Eleven respondents did not believe that it did. Other important themes that were mentioned included lack of service from vendor, lack of training from vendor, lack of consistency, lack of flexibility, lack of speed, lack of accuracy, and the inability to adapt this technology to existing equipment or sawmill. A comment listed several times suggests that the technology manufacturers do not understand hardwood sawmills and have simply tried to adapt softwood scanning technology unsuccessfully. Finally one respondent stated, “All that glitters isn’t gold!”

When asked what specific features an edger-optimizer, trimmer-optimizer, or automated grading system would need to have before they would install it in their sawmill, two closely related themes were low cost and short payback with 45 and 35 responses respectively. Three features specific to such equipment were accuracy (32 responses), ease of use (31 responses), and reliability (27 responses). One theme that is less of an equipment feature and more of a sawmill barrier is whether the new technology will fit into their existing mill. Eighteen responses were recorded. Eighteen respondents stated that the technology needs to be proven before they would install it. Five respondent said they would have to see it in operation before they would consider it. Maintenance issues were also important themes with 15 comments, while equipment breakdown and installation downtime received 9 comments. Other important comments included equipment flexibility (13 comments) which was closely related to the ability to change grading rules (10 comments). Other themes that occurred 10 or fewer times included speed, reduced employee numbers, maximizing yield, and ability to manually override. Thirteen respondents said that they were too small or not familiar with the technology to install it. Finally, one individual stated that *free* was a needed feature before he would install a scanning and optimizing system.

When asked if we have missed any of their concerns, most of their responses reiterated responses to earlier questions. Nine individuals stated that they were too small or too close to retirement to consider installing scanning and optimizing technology. Eight respondents commented specifically on the importance and need of future automated hardwood grading systems. Five responses suggested that we abandon the NHLA rules in favor of a simpler rule system or a rule system based on automated scanning technology. Three individuals stated that optimization was needed and necessary in the future. Several other comments reiterated the importance of low cost, flexibility, and payback. A few individuals commented on how the technology just wasn't for them. Consider the following statement, "Any production speed will cause more waste. I am not against these actions or what they mean. I operate with old technology, very happily thank you! Happy Trails." Others made statements praising such technology, "I see grading extremely important. I would be willing to participate in development of computerized grading." Finally, a response signed by Charlie stated, "I truly believe if we are going to stay in business for the long term optimization is inevitable."

Conclusions

This chapter developed a perspective on current and future scanning and optimizing technology in hardwood sawmills. These scanning and optimizing systems included current edger-optimizer technology (based on size and wane information), future edger-optimizer technology (based on size, wane, and surface defect information), and future automated grading systems (based on size, wane, and surface defect information).

Over 73 percent of responding companies believe that these types of scanning and optimizing technologies would help their sawmill. They believe it could help improve overall yield, recovery, consistency, and speed; however, many companies felt that this technology was too costly or that its payback was unknown.

Improved raw material recovery and *increased lumber revenues* were rated as the most important decision factors for current edger-optimizer systems. These high ratings may reflect partially on high raw material costs. Sawmills see the importance of producing the most from a log and manufacturing higher value lumber (upgrade) to increase overall revenue. These two factors were also rated significantly higher by large, NHLA, and technology companies as compared to their counterparts (alpha = 0.05). Non-NHLA and non-technology companies rated *initial cost* significantly higher than their counterparts. These companies may not have the necessary capital for scanning and optimizing technology investments. Both large and NHLA companies rated *availability of vendor support* significantly higher that their counterparts. In addition, NHLA companies rated *training from vendor* significantly higher. There were several significant differences between the three comparison groups involving various vendor relationships.

Nearly 50 percent of the respondents chose the lowest price category for current edger-optimizers with another 26 percent choosing the second lowest category. From comparisons with the non-response bias calls and conversations with the industry, this researcher believes that the *less than $100,000* category was often used as a default category. Respondents that were not familiar with this technology or aware of its capabilities may have selected the lowest cost category even though they would not consider installing the technology at this time. In hindsight, a sixth category, *would not install at this time*, might have alleviated this problem. Also, these acceptable costs may be skewed to the low side. A sawmill may be willing to pay more for scanning and optimizing equipment if they understand the full benefits and payback.

Manufacturers of edger-optimizers need to focus their promotion on the critical decision factors identified in this study. Production issues such as raw material recovery, lumber revenues, lumber quality, and lumber consistency were all highly rated. Edger-optimizers are designed to address these issues, yet adoption of this technology is low. One barrier is initial cost. The small sawmill segment of the hardwood sawmill industry will not be able to justify this technology based on cost; however, medium and large sawmills could justify the cost. Clear documented examples of return on investment are necessary to further promote adoption. Cost issues become less important when payback is clearly demonstrated.

Similar results were found with future edger-optimizer systems. *Improved raw material recovery* and *increased lumber revenues* were selected most frequently. Acceptable cost levels, however, were rated more evenly when compared to the current edger-optimizer systems. Sawmillers may see the advantage afforded by total defect information versus wane only information.

Concerning future automated grading systems, *accuracy of grading* was rated significantly higher than any other factor. This may suggest that the sawmill industry is apprehensive about this technology's ability. Other highly rated factors were *system lifespan* and *durability*. The hardwood sawmill is a harsh environment and equipment must be designed to withstand its conditions. Comparisons found *speed* and *training from vendor* rated significantly higher with large, technology, and NHLA companies.

This may reflect their production emphasis and experience with other equipment vendors. Small and non-NHLA companies rated *initial cost* significantly higher.

Nearly 80 percent of respondents choose the bottom two acceptable cost categories. A sawmill may be willing to pay more after the full capabilities of this technology have been demonstrated.

As with the edger-optimizer systems, manufacturers of future automated grading systems will have to focus their efforts on promotion. The ability of these systems to accurately grade hardwood lumber must be clearly demonstrated. Human graders are highly paid and often difficult to find. This in itself could drive the adoption of a proven automated grading system. Other features of the system such as integration into secondary manufacturing and customer confidence in grade tallies would help demonstrate a favorable result.

Through all of the comparisons for the different technologies, comparing NHLA members versus non-NHLA members generated the most significant differences. It may be possible that members of this organization set higher standards or demand more from their sawmill.

Finally, the responses to the open-ended questions verified the earlier data. High cost was the most frequent negative response. A parallel response was short payback and return on investment. Several respondents suggested a complete abandonment of NHLA rules in favor of a simpler automated grading rule system.

To promote the diffusion of this technology into the industry, equipment manufacturers must concentrate on the factors that were highly rated in this study. Demonstrating the ability of this equipment to improve raw material recovery and increase lumber revenues is paramount. In addition to demonstrating these technologies' abilities, cost issues must be addressed. High initial cost will preclude a segment of the industry; however, a favorable return on investment is of critical importance.

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CHAPTER 4: Future Scanning and Optimizing Technology: Modeling the Hardwood Sawmill System for Technology Adopters and Non-adopters

Introduction

The following chapter examines the decision-making process of hardwood sawmills as they consider future scanning and optimizing technology. The researcher conducted onsite interviews with hardwood sawmill owners and managers. The principle objective was to model the adoption decision process of future scanning and optimizing technology. Two distinctly different groups of hardwood sawmills were included to identify differences in their decision processes. These groups included hardwood sawmills that have adopted advanced scanning and optimizing technology and hardwood sawmills that have not adopted advanced scanning and optimizing technology. An initial premise of this research was that those sawmills with advanced scanning and optimizing technology were more innovative and more inclined to manage their sawmills from a systems perspective. These sawmills would view its various departments more equally. In contrast, sawmills that had not adopted advanced scanning and optimizing technology were thought to be less innovative and less likely to manage from a systems perspective.

The modeling technique used in this process was the Analytic Hierarchy Process (AHP). The AHP model is a mathematical theory for measurement and decision-making that was developed by Dr. Thomas Saaty during the mid-1970's (Expert Choice 1999). The strength of this modeling process is in its ability to analyze complex decision problems. It organizes the basic rationality by breaking a problem into its smaller constituent parts and uses simple pair-wise comparison judgements to develop priorities in each hierarchy (Harker & Vargas 1987). As a final step, the model generates a series of weights, which identify the most important constituent parts in the decision process.

The AHP falls into a class of models known as policy capturing models. Models such as these reveal the critical determinants of a judgement or set of judgements (Nakamoto, 1999). Explained in terms of scanning and optimizing technology, the AHP model can be used to identify the key criteria or attributes that will move the decision process in favor of technology adoption. After the development of a specific AHP model for an individual or group, it can be used as a normative model to predict outcomes as elements within the model change (Smith *et al.* 1995).

The use of the AHP has become widespread. Government agencies, consulting firms, and corporations are using the AHP to analyze complex planning and policy issues (Harker & Vargas 1987). Other applications of the AHP include design evaluation, technology implementation decisions, and quality decisions (Expert Choice 1999). Calantone et al. (1999) have recommended the AHP model as a new product screening decision support tool. Although ideas for new products cost nothing, the research and development of new products can be extremely expensive. This is exactly the case with current scanning and optimizing technology. Wood processing equipment manufacturers have spent millions of dollars developing these technologies without a complete knowledge of hardwood sawmill customers' expectations and needs. It is not suggested here that current scanning and optimizing technology has not been successful; however, a complete analysis of the decision and development process would have been beneficial. A decision support tool such as the AHP model could have been useful in the initial design process. Even though current scanning and optimizing technology is past the initial new product development stage, modeling the decision process with the AHP model can be useful for future scanning and optimizing technology development.

New manufacturing technology often presents some difficult choices. Future scanning and optimizing technology such as edger-optimizers and automated grading systems are examples. The adoption decision process involved with this technology is unclear. What processes do sawmill managers go through when they are deciding to adopt or not adopt future scanning and optimizing technology? What characteristics of the technology influence the decision process? What characteristics of the hardwood sawmill influence the decision process? What role does communication within the sawmill play in the decision process? These questions were examined through AHP modeling.

Objectives

The objectives of this chapter were:

1. Determine the important decision factors for the adoption of future scanning and optimizing technology in hardwood sawmills.

2. Using the Analytic Hierarchy Process, examine sawmill management's hardwood lumber scanning and optimizing technology adoption decision process based on a sawmill system's perspective.

3. Discern differences which may exist between adopters and non-adopters of future scanning and optimizing technology in hardwood sawmills.

Methodology

For this research, scanning and optimizing technology was classified into three groups including **current** scanning and optimizing technology, **advanced** scanning and optimizing technology, and **future** scanning and optimizing technology. **Current** scanning and optimizing technology is an all-encompassing term. It includes all of the currently available scanning and optimizing systems such as *bucking-optimizers, headrig-optimizers, edger-optimizers, trimmer-optimizers, grade mark readers,* and *automated sorting* systems. **Advanced** scanning and optimizing technology is more specific. It refers specifically to the most advanced and innovative systems currently available. These systems only partially optimize since decisions are based on profile information only (size and wane). These systems include edger-optimizers and trimmer-optimizers. Finally, **future** scanning and optimizing technology refers to prototype systems that are not commercially available. This technology is more advanced since it truly optimizes based on total defect information (profile, knots, splits, etc.). An example of this technology is the Auto-Grade system under development at Virginia Tech (Kline *et al.* 1998).

In the mail survey described in the previous chapters, scanning and optimizing technology in the hardwood sawmill was examined in the broadest sense. The goal was to determine the amount of scanning and optimizing technology currently used by the hardwood sawmill industry. In the AHP modeling portion of this research, scanning and optimizing technology was defined more specifically. Only sawmills that had **advanced** scanning and optimizing technology (edger-optimizers and trimmer-optimizers) were called adopters. These two types of scanning and optimizing technology are the most advanced commercially available systems for hardwood sawmills. Other forms of optimizing equipment such as headrig-optimizers and grade mark readers have been in use since the 1980s and are considered less innovative. An objective was to group the most innovative adopters into one model and group the non-adopters into another model. Building upon these two groups, this modeling research focuses on the adoption decision processes of **future** scanning and optimizing technology.

Population

The population of interest was hardwood sawmills. However, this population was viewed as two specific groups, hardwood sawmills that have adopted advanced scanning and optimizing technology and hardwood sawmills that have not adopted advanced scanning and optimizing technology.

Sample Frame

The sample frame consisted of 11 hardwood sawmills that had adopted advanced scanning and optimizing technology and 16 hardwood sawmills that had not adopted advanced scanning and optimizing technology. The sampling process was not random, but purposeful in nature. Patton (1990) identifies several sampling procedures. One such procedure called stratified purposeful sampling illustrates characteristics of particular subgroups of interest to facilitate comparisons. This was the principle idea behind selecting two groups, adopters and non-adopters. It is also important to note that these 27 hardwood sawmills were located in 7 states which covered the primary hardwood producing regions within the United States (Table 4-1). This resulted in models that were based on national data. The geographically broad sample area was also needed to identify a sufficient number of hardwood sawmills that had advanced scanning and optimizing technology.

Table 4-1: Case Study Interviews by State

State	# Mills Visited	Adopters	Non-Adopters
Wisconsin	9	2	7
Virginia	2	1	1
West Virginia	1	1	0
Maryland	1	1	0
Pennsylvania	6	2	4
Tennessee	6	2	4
North Carolina	2	2	0
Total	27	11	16

AHP Model Development

The development of the AHP model involved several steps including the initial mail survey, factor reduction, and model construction. Each step was dependent upon the previous to build the model's theoretical foundation.

Mail Survey

The previous chapters described a nation wide mail survey conducted in the fall of 1999. Questionnaires were sent to over 2000 hardwood sawmills. Information was collected on hardwood sawmill demographics and production. In addition, seven point Likert scales were used to collect information on scanning and optimizing technology. The mail survey scale question that was used to build the AHP model examined advanced edger-optimizer systems. Respondents rated the importance of 20 factors involved in the decision to adopt currently available edger-optimizer systems (Table 4-2). Experts from Virginia Tech, the USDA Forest Service Southern Research Station, and the forest products industry were involved in the development of this factor list.

Table 4-2: Factor Importance Ratings for Current Edger-Optimizers

Factor	Mean Importance
Improved Raw Material Recovery	6.5
Increased Lumber Revenues	6.5
System Lifespan	6.0
Improved Lumber Quality	5.9
Ability to Upgrade	5.9
Availability of Vendor Support	5.8
Increased Production Levels	5.8
Improved Lumber Consistency	5.7
Ease of Use	5.7
Initial Cost	5.7
Maintenance Costs	5.2
Existing Mill Layout Restrictions	5.2
Training from Vendor	5.1
Operational Costs	5.1
Installation Down Time	4.8
Advice from Production Supervisors	4.7
Training of New Operators	4.6
Advice from Customers	4.4
New Mill Installation	4.1
Advice from Sales Department	3.7

Factor Reduction

The AHP model structure used in this research is capable of incorporating up to nine decision factors. As the number of decision factors increases, so does the number of paired comparisons. Beyond the nine-factor limit, the number of comparisons becomes difficult for a respondent to perform in a reasonable amount of time in a meaningful manner. Twenty adoption decision factors were compiled for the mail survey (Table 4-2). Each of these adoption decision factors was included because of its importance. The objective was to build the AHP model upon these factors. A method of data reduction was needed to reduce the number of adoption decision factors but maintain the underlying meanings of the 20 factors. To accomplish this, factor analysis was used. Factor analysis identifies underlying factors that explain the pattern of correlation within a set of observed variables (Hair *et al.* 1992). In our case, correlated adoption decision factors were identified. The principal components analysis method with varimax rotation was used. An eigenvalue criterion of 1.0 was used to determine the number of underlying decision factors. The principal components procedure was chosen for its ability to summarize the original information (20 factors) into a minimum number of factors while maintaining most of the original information. Varimax rotation was chosen to provide a clearer separation of the factors (Hair *et al.* 1992). The SPSS® Statistical Data Analysis package was used to perform the analysis.

Model Construction

The AHP model uses quantitative and qualitative data to aid in the decision process. By dismantling a decision, with all of its associated variables, into small manageable pieces, a decision-maker is able to examine and understand the decision process. The AHP modeling process can be broken into three principle processes which include decomposition, comparative judgements, and synthesis of priorities (Harker & Vargas 1987). These three steps are key in the modeling process. Decomposition allows for a complex decision problem to be broken into simple manageable parts. The comparative judgements process results in the formation of a matrix from pair-wise comparisons of the relative importance of the elements in one hierarchy level with respect to the elements one level up. The synthesis process generates a composite of the elements at the lowest hierarchy level (Harker & Vargas 1987). Figure 4-1 provides an example of the AHP model applied to the future scanning and optimization adoption decision process. It illustrates the three step modeling process of decomposition, comparative judgements, and synthesis of priorities.

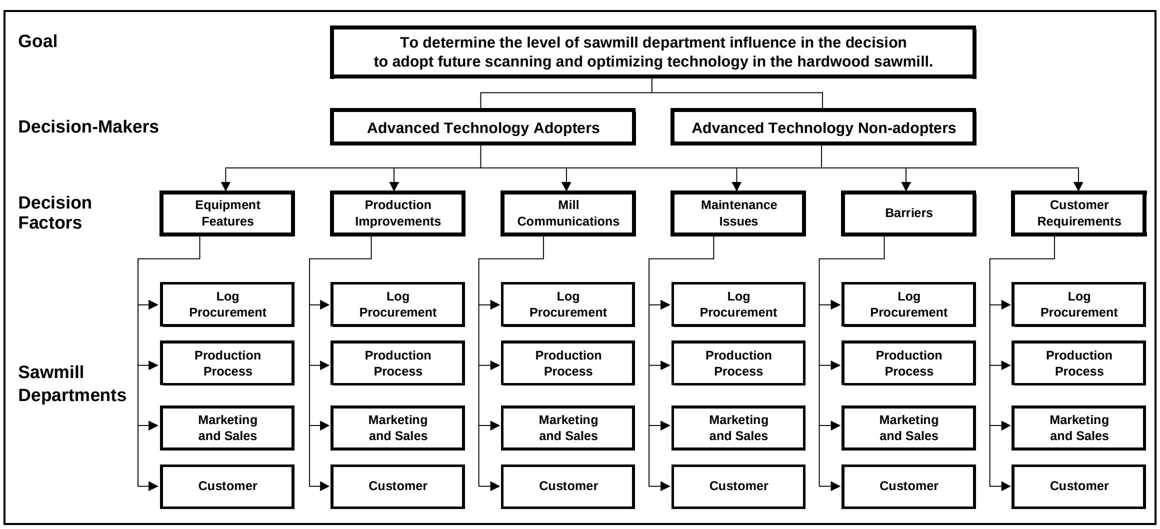

Figure 4-1: AHP Model Structure, Future Scanning and Optimizing Technology Example

Decomposition

Figure 4-1 can be broken into four major levels including the *goal* level, the *decision-makers* level, the *decision factors* level, and the *sawmill departments* level. The goal level describes the decision under investigation. In our model, the goal was to determine the level of sawmill department influence in the decision to adopt future scanning and optimizing technology in the hardwood sawmill. In other words, how influential are the opinions of the different sawmill departments.

The second level is the decision-makers level. In our case, the decision-makers level is comprised of two groups: hardwood sawmills that have adopted advanced scanning and optimizing technology and hardwood sawmills that have not adopted advanced scanning and optimizing technology.

The third level consists of the adoption decision factors or criteria that are important in the decision process. These were generated by the factor analysis of the mail survey data. At this level, a series of pair-wise comparisons are made between all factors which in turn weight the decision factors as to their importance (Figure 4-1). The weights across all decision factors sums to one.

Level four, the sawmill departments level, is key for the sawmill systems analysis. Level four describes a generic way of viewing a typical sawmill. Figure 4-2 shows four sawmill departments that would typically be involved in sawmill management decisions. Experts from Virginia Tech and from the hardwood sawmill industry agreed that this four-part model accurately described a generic hardwood sawmill. This systems level examines pair-wise comparisons between each sawmill department as they are influenced by each decision factor one level up. Pair-wise comparisons at this level are performed six times, one for each decision factor (Figure 4-1)

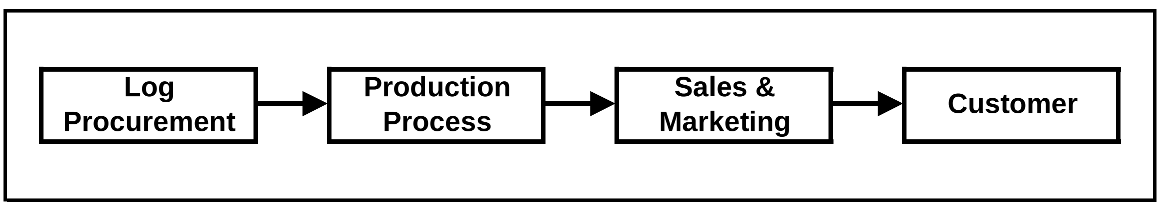

Figure 4-2: Generic Departmental Breakdown of a Typical Hardwood Sawmill

The AHP model has the ability to analyze a single case or multiple case data. The hardwood sawmill models generated in this research are multiple case models with 11 data sets in the advanced scanning and optimization adopter model and 16 data sets in the advanced scanning and optimization non-adopter model. In multiple case models, the data sets are combined and averaged using geometric means.

Comparative Judgements

The decomposition process clearly demonstrates the hierarchy within the AHP model. The comparative judgement process demonstrates the role of pair-wise comparisons in the decision process (Figure 4-1). These pair-wise comparisons generate the necessary data to build the vectors and matrices needed in the *synthesis of priorities*, the final step of the AHP modeling process.

The first matrix results from the pair-wise comparisons at the decision factors level. This matrix is called the *decision factor priority vector*. In our case, this vector is a 6x1 matrix of values that weight the importance of each decision factor relative to one another. These individual weights are normalized to provide a relative scale. Normalization involves summing the original column vector and dividing each original weight by the total sum. Normalization assures that the final weights sum to one.

The second matrix results from the pair-wise comparisons at the sawmill departments level with respect to each decision factor one level up. In our case, these six vectors are combined into a matrix called the *sawmill department priority vectors*. This is a 4x6 matrix of values that weight the importance of each sawmill department relative to one another with respect to each decision factor. To achieve the desired outcome, this vector is normalized during the AHP modeling process.

Synthesis of Priorities

The synthesis process weights the elements at the lowest hierarchy level, the sawmill departments level. These weight values are called the *final priority vector*. The *final priority vector* results from the multiplication of the *decision factor priority vector* (matrix 1) with the *sawmill department priority vectors* (matrix 2). This results in a 4x1 matrix. The *final priority vector* satisfies the model goal. It weights each sawmill department based on its influence in the decision to adopt future scanning and optimizing technology.

Data Collection

The data collection during the case studies involved personal interviews at the participating hardwood sawmills. Interviews were scheduled with the primary equipment decision-maker at the sawmill. In most cases the primary equipment decision-maker was the sawmill owner or the sawmill manager. The meeting typically lasted less than one hour; however, several mill visits lasted several hours. In those cases the interviewee spent a great deal of time describing the sawmill and his experience or opinions of scanning and optimizing technology. Many of the interviews also included a mill tour which added to the qualitative value of the interview.

Each interview opened with an explanation of the research project. Several open-ended questions were asked to put the interviewee at ease (Appendix B). Following the open-ended questions, the interviewee was asked to complete a written questionnaire (Appendix B). Fifty-one paired comparisons were made by the interviewee including 15 at the decision factors level and 36 at the sawmill departments level. The questionnaire was developed directly from the model shown in Figure 4-1. The format was written for the AHP modeling process (Saaty *et al.* 1993). The questionnaire was reviewed and improved after consultation with experts at Virginia Tech. After this review, the questionnaire and the interview format was successfully pre-tested with five hardwood sawmills located in Virginia and West Virginia.

Data Analysis

The AHP model uses matrix algebra to solve the decision objective. Expert Choice™ is a PC driven decision support software package built for the AHP modeling process (Expert Choice 1993). A model as shown in Figure 4-1 was constructed within the Expert Choice program. This model incorporated data from the advanced scanning and optimizing adopters and non-adopters. The pair-wise comparisons from the written interview questionnaire forms were entered into the model in Expert Choice. Expert Choice was then used to generate the final priority vectors and to conduct sensitivity analysis.

Inconsistency Ratios

For each set of pair-wise comparisons performed, Expert Choice provided a rating called an inconsistency ratio. This ratio is a measure of how consistent the respondent was in his or her pair-wise ratings. For example, if A was rated 2 times greater than B, and B was rated 2 times greater than C, then A should be rated 4 times greater than C. There is a certain amount of inconsistency in any respondent's answers. Saaty (1980) suggests that an inconsistency ratio of less than 0.1 is excellent. In both the adopter and non-adopter models, the inconsistency ratios were 0.03 or lower. These ratios were well below the acceptable level indicating no significant inconsistencies. In this way the AHP deviates from other decision analytic methods in that the AHP model formally addresses inconsistency issues (Harker & Vargas 1987).

Results and Discussion

Factor Reduction Results

Factor analysis was used to reduce the number of decision factors from the mail survey. Correlated adoption decision factors were identified. Using the principal components analysis method with varimax rotation, five underlying components were identified. Table 4-3 shows the rotated component matrix with the factor loadings. To determine which components (column) a factor loaded into, a minimum significance level of 0.3 was established; however, no factor in our analysis loaded below 0.5. A general rule states that 0.3 is significant, 0.4 is more important, and 0.5 is very significant (Hair *et al.* 1992).

Table 4-3: Factor Analysis Rotated Component Matrix with Factor Loadings

	Component				
	1	2	3	4	5
Initial Cost	.229	.062	-.200	.094	.634
Training of New Operators	.203	.051	.365	.498	.160
Operational Costs	.126	.150	.187	.781	-.001
Installation Down Time	.219	-.003	.059	.735	.177
Maintenance Costs	.227	.057	.120	.817	.103
Improved Raw Material Recovery	.283	.810	-.039	-.080	.141
Increased Production Levels	-.014	.693	.220	.323	-.072
Increased Lumber Revenues	.227	.791	.066	.031	.071
New Mill Installation	-.135	.108	.506	.279	.452
Existing Mill Layout Restrictions	-.074	.028	.298	.134	.754
Advice from Sales Department	.202	-.031	.718	.196	.172
Improved Lumber Quality	.159	.564	.510	.067	-.016
Advice from Customers	.241	.204	.678	.198	-.115
Improved Lumber Consistency	.302	.553	.514	.087	.014
Advice from Production Supervisors	.389	.248	.639	.089	.020
Training from Vendor	.744	.058	.391	.141	.080
Ease of Use	.704	.180	.197	.316	.033
Availability of Vendor Support	.795	.170	.114	.207	.101
Ability to Upgrade	.615	.363	.196	.103	.152
System Lifespan	.577	.361	.098	.335	.126

The original 20 factors were organized into five groups as dictated by their loadings (Table 4-4). In one case, it was decided to move the original factor, *new mill installation*, from its highest loaded group to its second highest loaded group. The researchers determined that this original factor conceptually fit better with the second group. Cronbach's Alpha was calculated for each of the resulting groups. These values are shown in parenthesis in Figure 4-4.

After the groups were determined appropriate decision factor names were added. Faculty from Virginia Tech were consulted to identify decision factor names representative of the underlying group. These final decision factor names included *equipment features*, *production improvements*, *mill communications*, *maintenance issues*, and *barriers*.

Table 4-4: Factor Reduction and Classification

Factor 1 (.85) Equipment Features	Factor 2 (.81) Production Improvements	Factor 3 (.74) Mill Communications
Training From Vendor	Improved Raw Material Recovery	Advice From Sales Department
Ease of Use	Increased Production Levels	Advice From Customers
Availability of Vendor Support	Increased Lumber Revenues	Advice From Production Supervisors
Ability to Upgrade	Improved Lumber Quality	
System Lifespan	Improved Lumber Consistency	
Factor 4 (.77) **Maintenance Issues**	**Factor 5 (.43)** **Barriers**	***Factor 6*** ***Customer Requirements***
Training of New Operators	Initial Cost	*Size Requirements*
Operational Costs	New Mill Installation	*Grade Requirements*
Installation Downtime	Existing Mill Layout Restrictions	*Sorting Requirements*
Maintenance Costs		
Cronbach's Alpha values for each factor grouping are shown in parentheses		

Review of these five factors found that each was closely related to production. The intent of the model was to examine the hardwood sawmill from a systems perspective. After consultation with experts at Virginia Tech, a sixth factor, *customer requirements*, was added to broaden the scope of the model to its original intent (Table 4-4). Since the AHP model anatomy considers each factor independently, any of these six factors could be removed to determine how the model performs in its absence.

Modeling Example

The following example demonstrates the AHP. Data from the advanced scanning and optimizing technology adopters were used to show how the synthesis of priorities were calculated.

The *decision factor priority vector* results from the pair-wise comparisons at the decision factor level. This vector is a 6x1 matrix of values that weights the importance of each decision factor relative to one another (Table 4-5). These individual weights are normalized to provide a relative scale. Normalization involves summing the original column vector and dividing each original weight by the total sum. Normalization assures that the final weights sum to one.

Table 4-5: Decision Factor Priority Vector

Decision Factors	Priority Vector
Equipment Features	0.114
Production Improvements	0.286
Mill Communications	0.075
Maintenance Issues	0.206
Barriers	0.112
Customer Requirements	0.207

The *sawmill department priority vectors* result from the pair-wise comparisons at the sawmill departments level with respect to each decision factor one level up. These six vectors combine into a 4x6 matrix of values that weight the importance of each sawmill department relative to one another with respect to each decision factor. To achieve the desired outcome, each vector is normalized during the AHP modeling process (Table 4-6).

Table 4-6: Sawmill Department Priority Vector

Sawmill Department	Decision Factors					
	Equipment Features	Production Improvements	Mill Comm.	Maintenance Issues	Barriers	Customer Requirement
Log Procurement	0.012	0.039	0.010	0.020	0.016	0.023
Production Process	0.044	0.150	0.036	0.125	0.066	0.044
Sales and Marketing	0.032	0.052	0.016	0.037	0.018	0.069
Customer	0.027	0.045	0.012	0.024	0.014	0.071

Sawmill Department	Normalized Decision Factors					
	Equipment Features	Production Improvements	Mill Comm.	Maintenance Issues	Barriers	Customer Requirement
Log Procurement	0.104	0.136	0.135	0.097	0.140	0.111
Production Process	0.383	0.524	0.486	0.607	0.579	0.213
Sales and Marketing	0.278	0.182	0.216	0.180	0.158	0.333
Customer	0.235	0.157	0.162	0.117	0.123	0.343

The *final priority vector* results from the multiplication of the *decision factor priority vector* (Table 4-5) with the *sawmill department priority vectors* (Table 4-6). The *final priority vector* is a 4x1 matrix that holds the composite priorities at the model's lowest level, the sawmill departments. Figure 4-3 shows the multiplication process that generates the *final priority vector*.

$$
\begin{array}{l}
\\
\text{Log Procurement} \\
\text{Production Process} \\
\text{Sales and Marketing} \\
\text{Customer}
\end{array}
\begin{array}{c}
\begin{array}{cccccc}
\text{Equipment Features} & \text{Production Improvements} & \text{Mill Communications} & \text{Maintenance Issues} & \text{Barriers} & \text{Customer Requirements}
\end{array} \\
\begin{pmatrix}
0.104 & 0.136 & 0.135 & 0.097 & 0.140 & 0.111 \\
0.383 & 0.524 & 0.486 & 0.607 & 0.579 & 0.213 \\
0.278 & 0.182 & 0.216 & 0.180 & 0.158 & 0.333 \\
0.235 & 0.157 & 0.162 & 0.117 & 0.123 & 0.343
\end{pmatrix} \\
\text{Matrix of Sawmill Department Priority Vectors}
\end{array}
\underbrace{\begin{pmatrix}
0.114 \\ 0.286 \\ 0.075 \\ 0.206 \\ 0.112 \\ 0.207
\end{pmatrix}}_{\text{Decision Factor Priority Vector}}
=
\underbrace{\begin{pmatrix}
0.120 \\ 0.463 \\ 0.224 \\ 0.192
\end{pmatrix}}_{\text{Final Priority Vector}}
\begin{array}{l}
\text{Log Procurement} \\
\text{Production Process} \\
\text{Sales and Marketing} \\
\text{Customer}
\end{array}
$$

Figure 4-3: Final Priority Vector for the Future Scanning and Optimization Adoption Decision Process, Adopter Results

Model Results

The AHP model generates two important vectors including the *decision factor priority vector* and the *final priority vector*. These two vectors identify the relative importance of the decision factors and sawmill departments in our model. The following sections will examine the results of these vectors for the adopter and non-adopter models.

Decision Factor Priority Vectors

The decision factor priority vector weights the model decision factors by their importance. The higher the weighting, the more important that decision factor was in the overall model decision. Figure 4-4 provides the decision factor priority vectors for the adopter and non-adopter models.

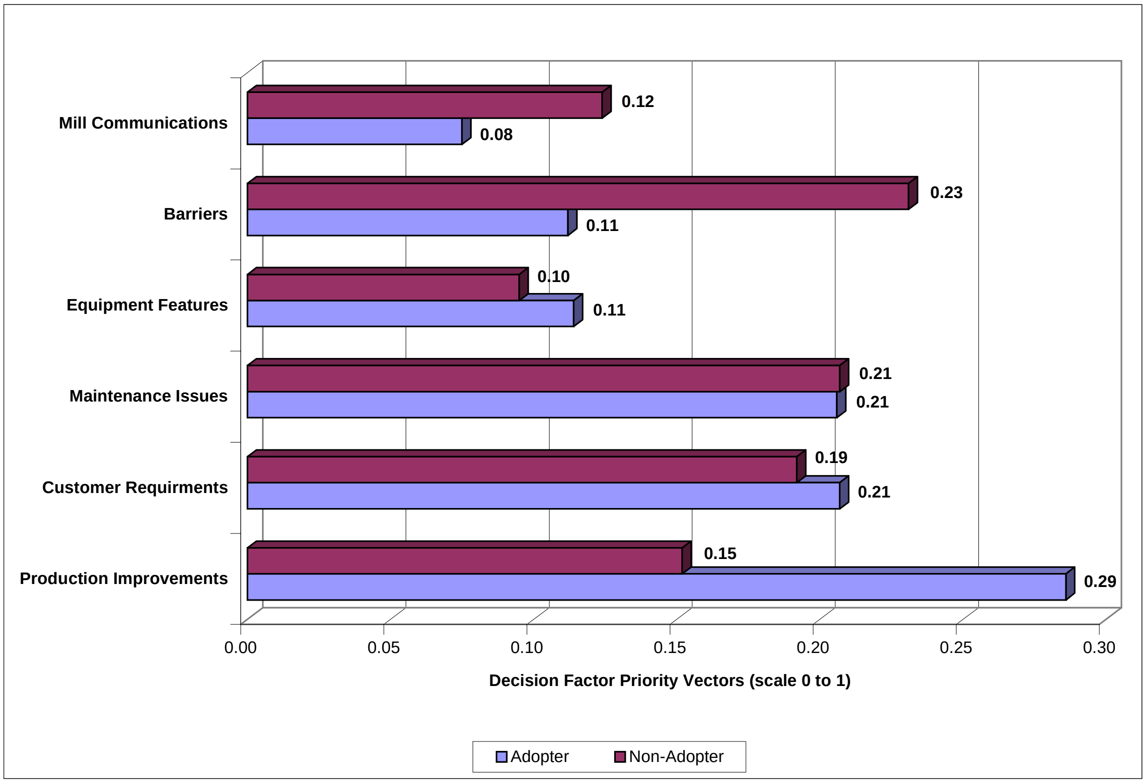

Figure 4-4: Adopter and Non-Adopter Decision Factor Priority Vectors

Production Improvements was rated highest for adopters. If we examine the original corresponding factors, *increased lumber revenues*, *increased production levels*, and *improved raw material recovery* were all highly rated factors in the mail survey portion of this research. Several differences are evident between the adopter and non-adopter groups. *Production Improvements* was rated higher for adopters than the non-adopters. This was contrary to the expected results. It was initially expected that the adopters were managed more from a systems perspective. Here increased production would be a result of this management philosophy and not a driver of it. *Mill communications* is higher for non-adopters. This is also contrary to the expected results. This could be explained by the fact that many of the non-adopters were small companies. The mill owner or manager often serves many roles in these companies and is in constant contact with the employees throughout the sawmill. *Barriers* was rated higher by the non-adopters. Two factor components for *barriers* were i*nitial cost* and *existing mill layout restriction*. The large capital requirements for the purchase of future scanning and optimizing technology restrict many small companies. In addition, the large size of this equipment may prohibit small mills from adopting it because of space restrictions. *Equipment features*, *maintenance issues*, and *customer requirements* were rated similarly for adopters and non-adopters (Figure 4-4). It is important to note that c*ustomer requirements* was highly rated. This adds validity to our decision to include this decision factor.

Final Priority Vector

The final priority vector weights the sawmill departments by their overall influence in the decision to adopt or not adopt future scanning and optimizing. The higher the weighting, the more important that department was in the overall adoption decision (Figure 4-5).

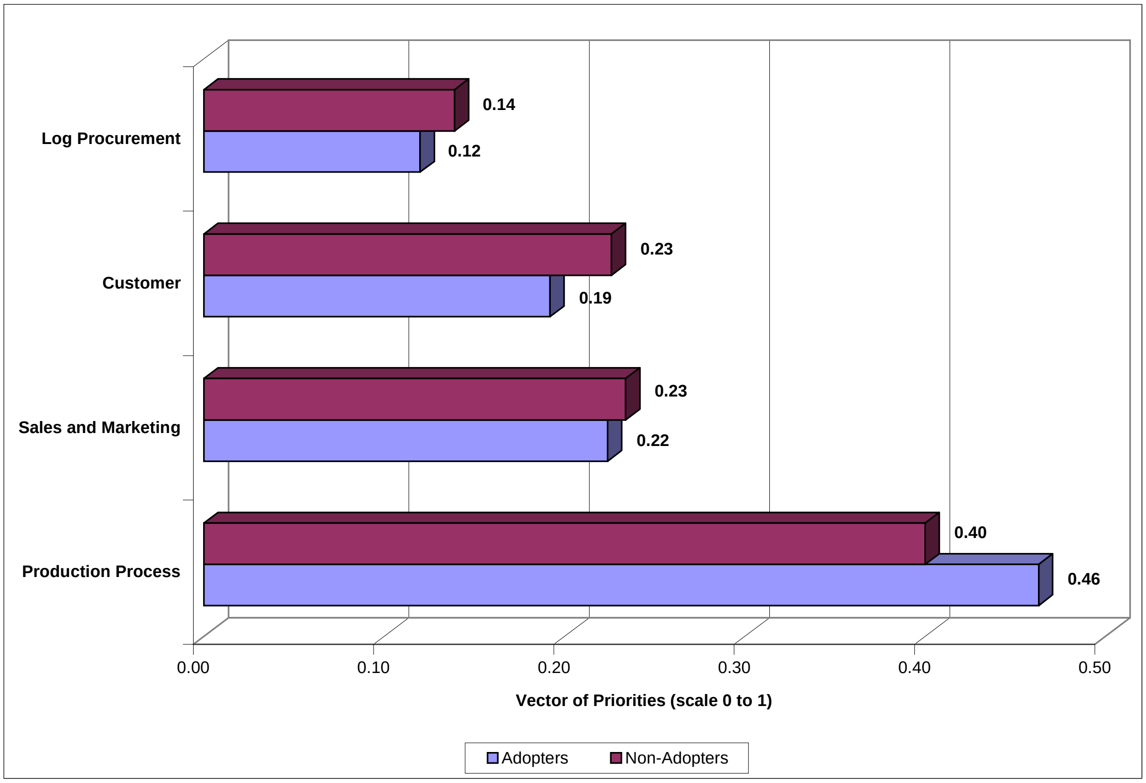

Figure 4-5: Influence of Sawmill Department: Adopters versus Non-Adopters

Paralleling the decision factor priority vector results, *production process* (the production department) was rated the highest by adopters and non-adopters. This supports the production philosopy in the wood products industry. It was initially expected that the adopters were managed more from a systems perspective. In other words, the four department ratings would be more evenly distributed for the adopters than the non-adopters. In fact, the opposite was true. Non-adopters rated the four sawmill departments more evenly than the adopters. As with the decision factor priority vectors, this could be a result of sawmill management anatomy. The owner or sawmill manager of a small sawmill is in contact with or is the primary employee in many or all of these departments. This individual may see more equal importance in each department.

Compiled Models

To summarize the data for adopters and non-adopters, Figure 4-6 provides the final AHP model structure for adopters and non-adopters. Decision factor priority vectors and sawmill department priority vectors are shown. The model follows the same structure shown in Figure 4-1, and provides the final decision values for the two groups.

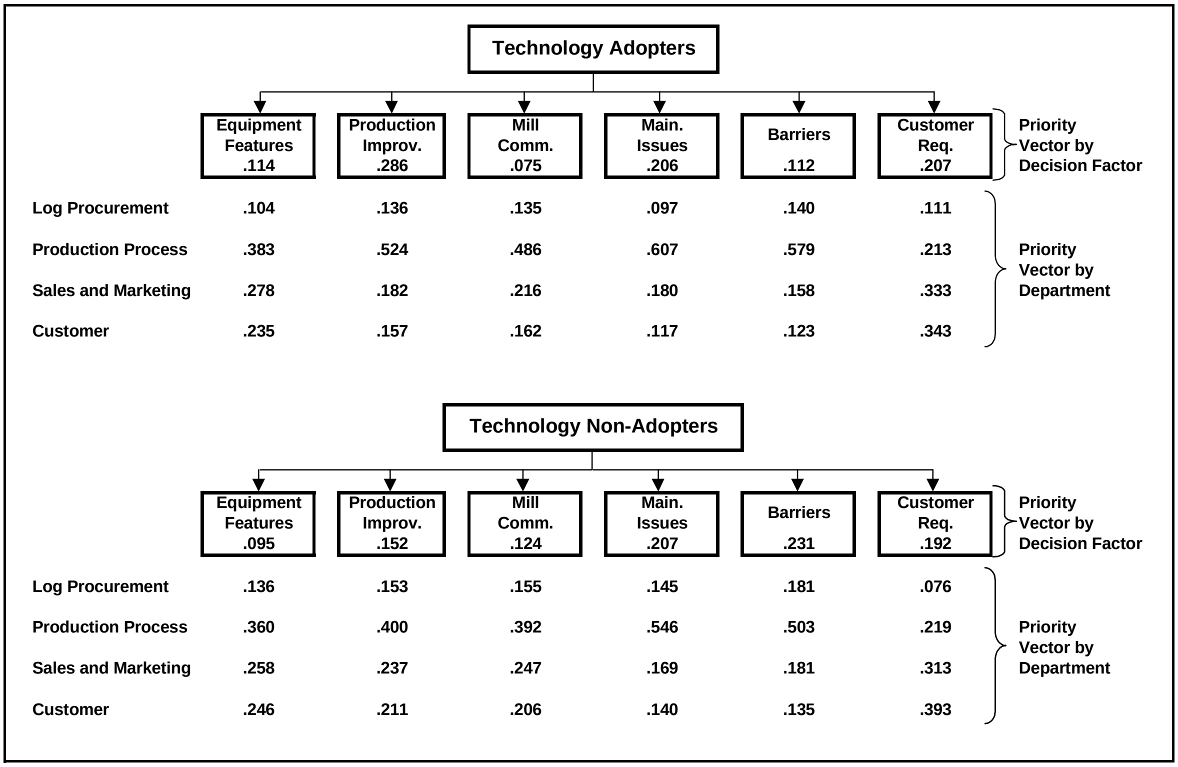

Figure 4-6: Final AHP Decision Models for Technology Adopters and Non-Adopters

Figure 4-6 depicts the data at a more detailed level. We are able to see each department influence with respect to each decision factor. It was stated earlier that the *production process* department was found to be more influential with the adopter group. This is shown in more detail with the department weights represented for each decision factor. A similar but opposite trend is shown for the *log procurement* department in the non-adopter group.

Decision Factor Manipulation

Previously, the factor analysis method was described to explain how the final decision factors were determined. To meet the initial intent of the study, an additional decision factor, *customer requirements*, was added to the model. This decision factor produced a balanced model when viewed from a systems perspective. To demonstrate the flexibility of the AHP model, *customer requirements* was removed. In this way, one can see how the model performs with only the remaining 5 decision factors.

Figure 4-7 shows the decision factor priority vector for the four models including adopters, non-adopters, 5 factor adopters, and 5 factor non-adopters. The final weights of the 5 factor models are greater. Normalization requires the weights to sum to one; however, the weights did not necessarily increase proportionally.

If *customer requirements* was no longer a decision factor in the decision process for future scanning and optimizing technology, several changes occur in the model. For non-adopters, *barriers* becomes even more important. If customer requirements are not included to drive technology adoption, issues such as the high initial cost of technology become even more important. For adopters, *production improvements* becomes more influential with the absence of customer requirements (Figure 4-7). This further demonstrates the production philosophy.

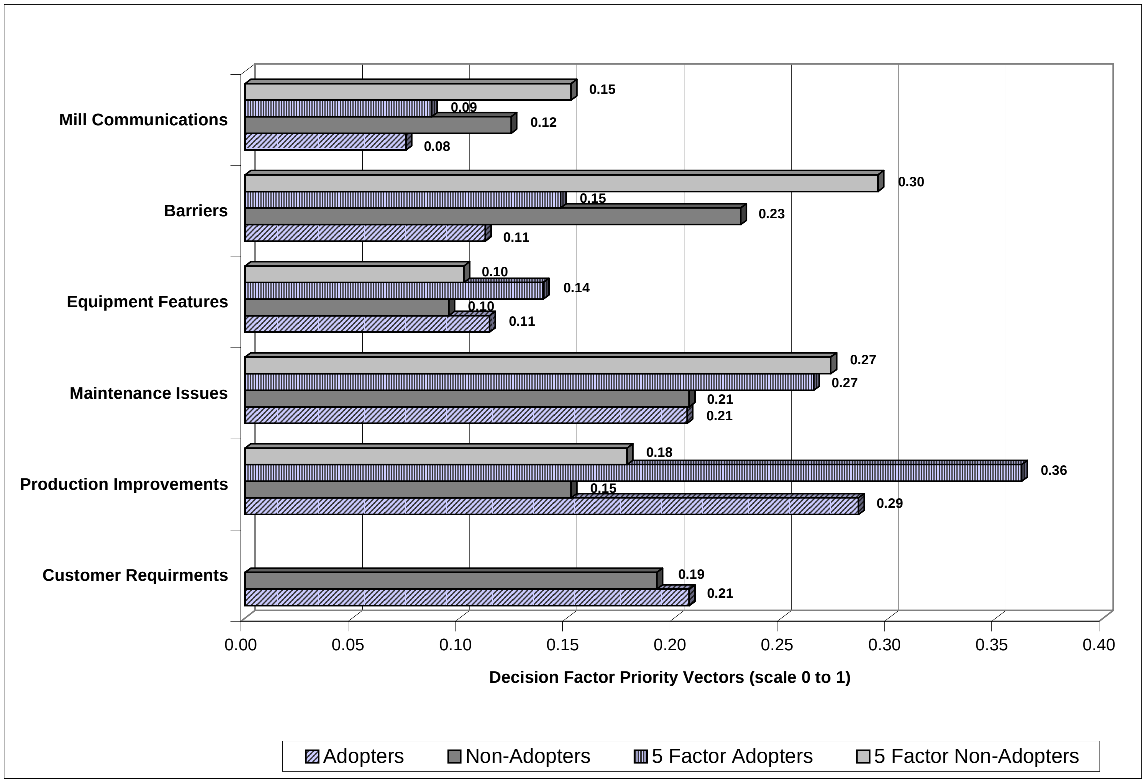

Figure 4-7: Decision Factor Priority Vector: Five Factor Comparison

Figure 4-8 shows how the influences of the sawmill departments change when *customer requirements* is no longer a decision factor in the adoption decision process of future scanning and optimizing technology. Both the *customer* and *sales and marketing* departments become less influential. The *log procurement* and *production process* departments become more influential.

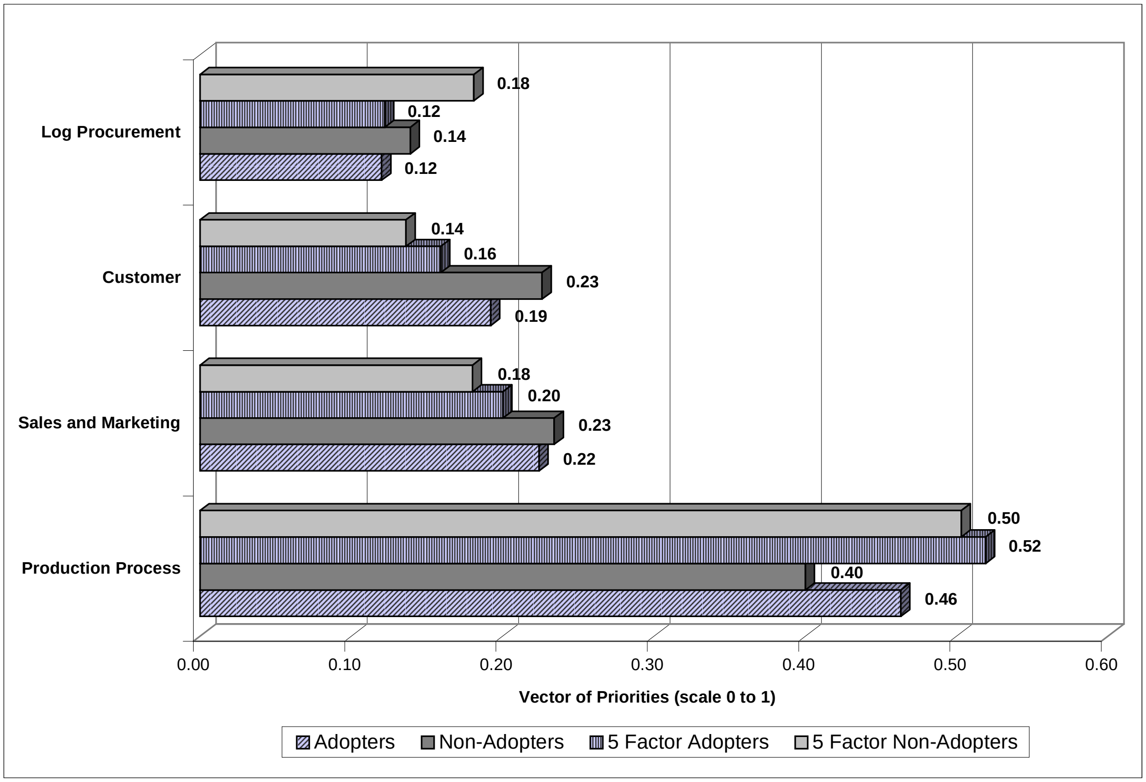

Figure 4-8: Influence of Sawmill Departments: Five Factor Model Comparison

Sensitivity Analysis

Sensitivity analysis is used to investigate the sensitivity of the sawmill departments to changes in the priorities of the decision factors. In other words, will a sawmill department become more influential in the decision to adopt future scanning and optimizing technology if certain decision factors become more or less important.

Adopters

Figure 4-9 through Figure 4-14 graphically represent sensitivity analysis for the adopters group. These figures, called sensitivity graphs, are generated by Expert Choice. The vertical line represents the decision factor under analysis. As this decision factor becomes more important (i.e. moved right on the X-axis), its intersection with the slope of the four sawmill department lines show if the department influence increases or decreases.

Figure 4-9 shows the sensitivity analysis of the *equipment features* decision factor. The priorities for the sawmill departments are on the Y-axis readings where the vertical line intersects the slanting sawmill department lines. The current priority for the decision factor is where the vertical line intersects the X-axis. The slope of the sawmill department lines indicates the degree influence change as the importance of the decision factor increases or decreases.

As the decision factor, *equipment features*, becomes more important, the production process and the log procurement departments become less influential while the sales and marketing and the customer departments become more influential. If the equipment features of future scanning and optimizing technology allow a hardwood sawmill to better serve a customer's needs, the influence of these two departments becomes more important.

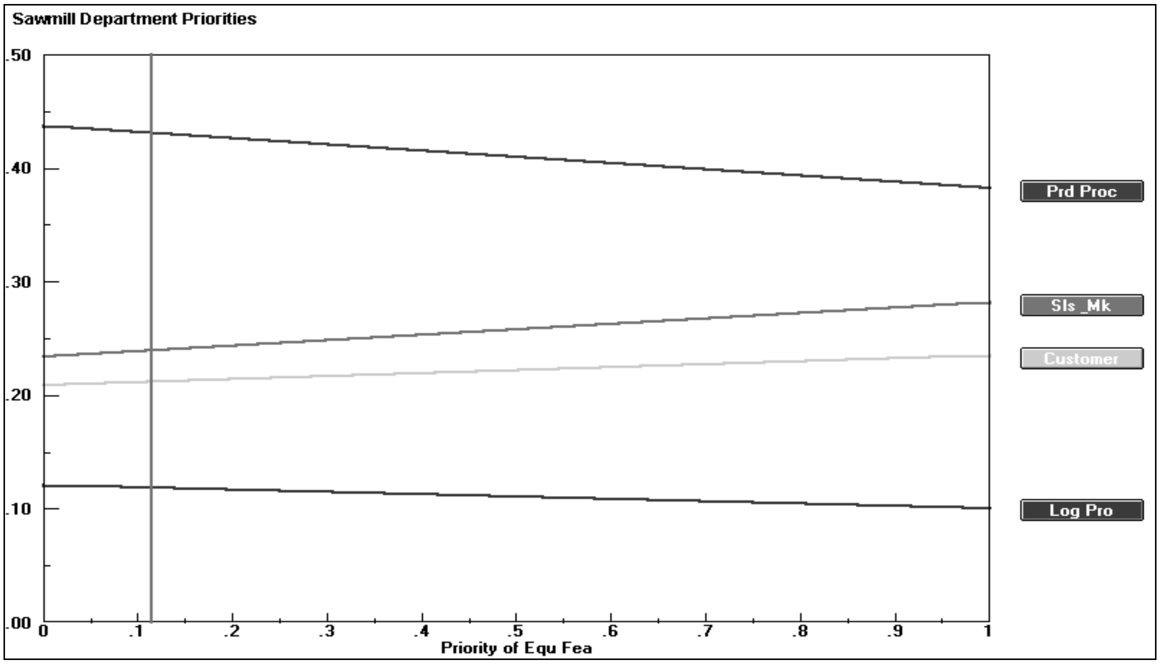

Figure 4-9: Adopter Sensitivity Analysis for Equipment Features

As the decision factor, *production improvements*, becomes more important, the production process and the log procurement departments become more influential while the sales and marketing and the customer departments become less influential (Figure 4-10). The log procurement and the production process departments are directly related to production improvements. Given the production mindset of adopters, it is not surprising that the influence of these two departments increases.

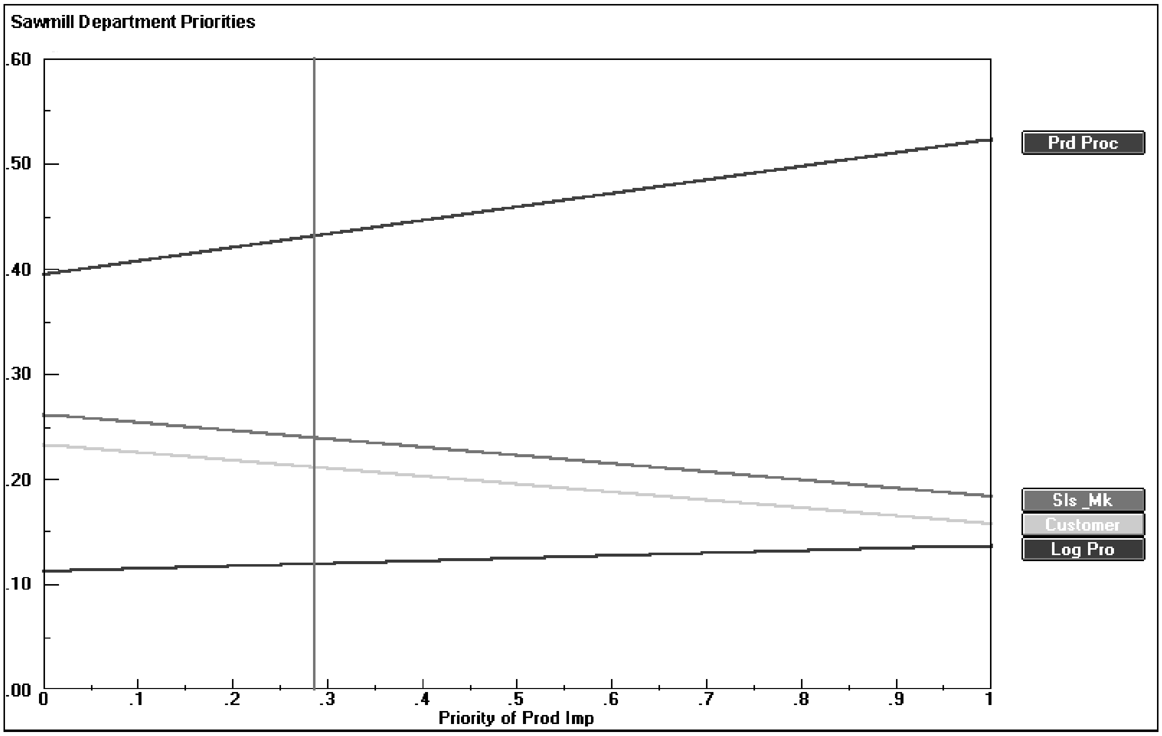

Figure 4-10: Adopter Sensitivity Analysis for Production Improvements

As the decision factor, *mill communications*, becomes more important, the production process and the log procurement departments become more influential while the sales and marketing and the customer departments become less influential (Figure 4-11). The customer may not be considered a part of the overall communication within the sawmill. The slopes of these lines are relatively small. Little change would occur with changes in the decision factor.

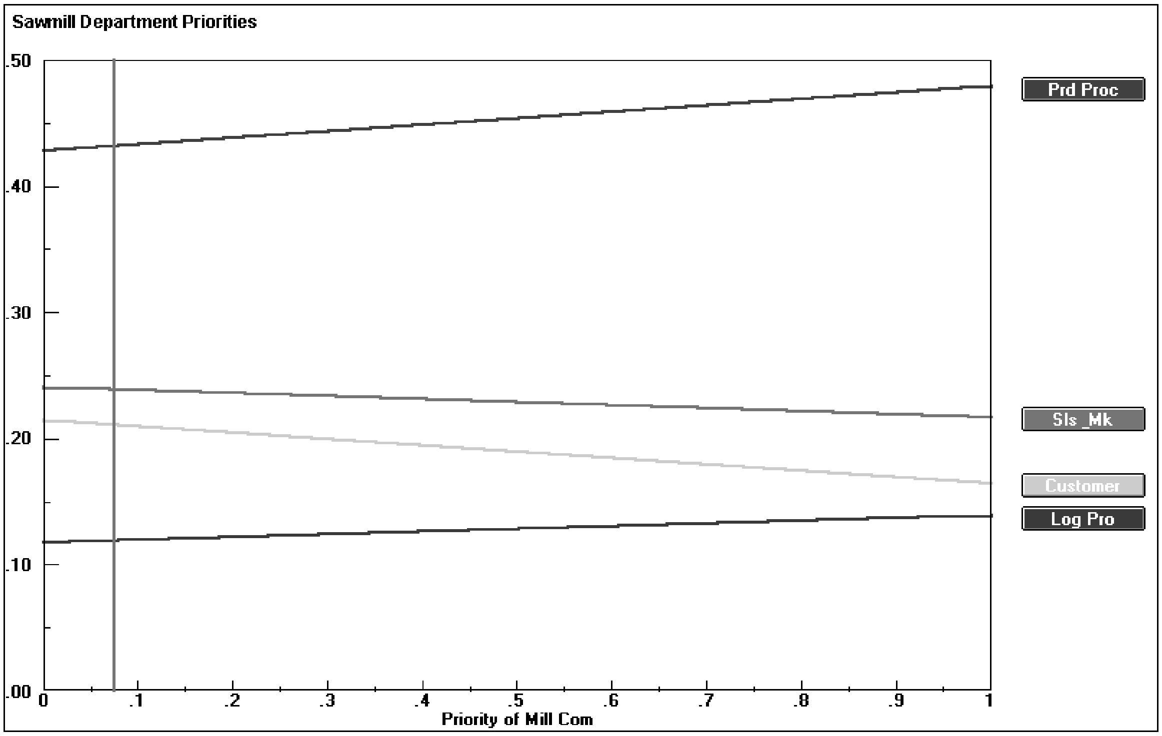

Figure 4-11: Adopter Sensitivity Analysis for Mill Communications

As the decision factor, *maintenance issues*, becomes more important, the production process department becomes more influential while the sales and marketing, the customer, and the log procurement departments become less influential (Figure 4-12). Maintenance issues are critical for production. Downtime during normal operations will reduce overall production improvements. The level of slope in the production process department line demonstrates its perceived importance.

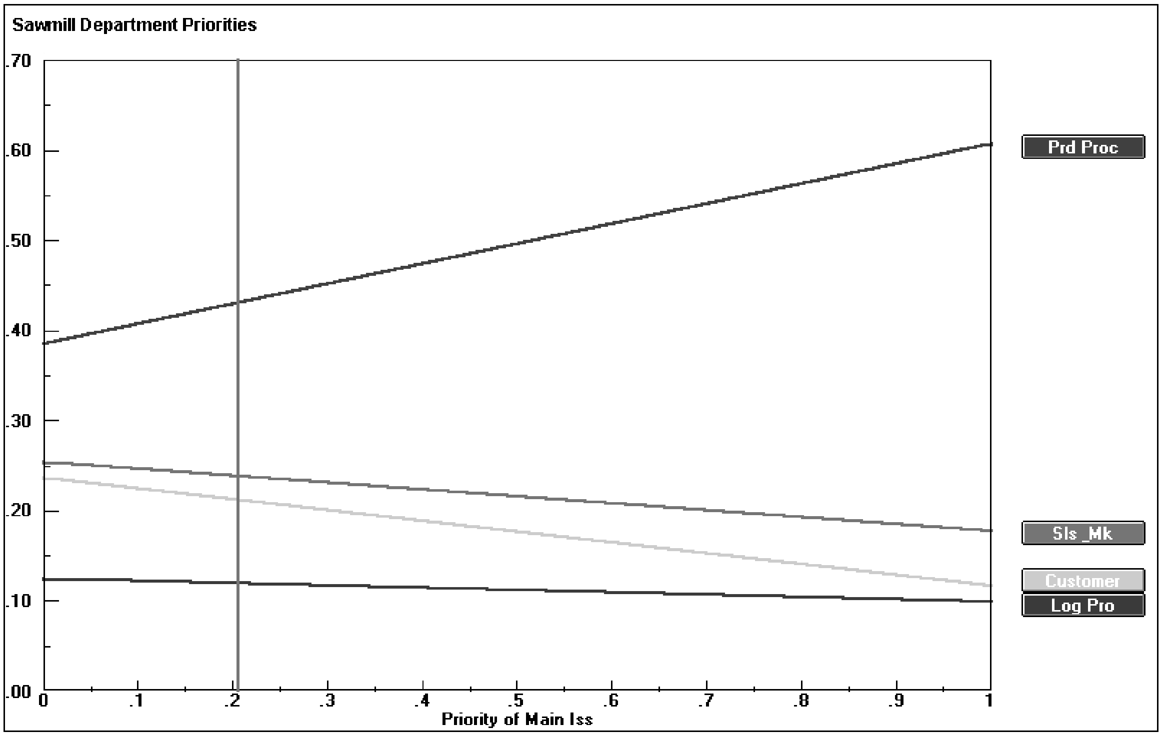

Figure 4-12: Adopter Sensitivity Analysis for Maintenance Issues

As the decision factor, *barriers*, becomes more important, the production process and the log procurement departments become more influential while the sales and marketing and the customer departments become less influential (Figure 4-13). If barriers such as initial cost become more important, the respondents may see increases in production as a way of offsetting this cost barrier.

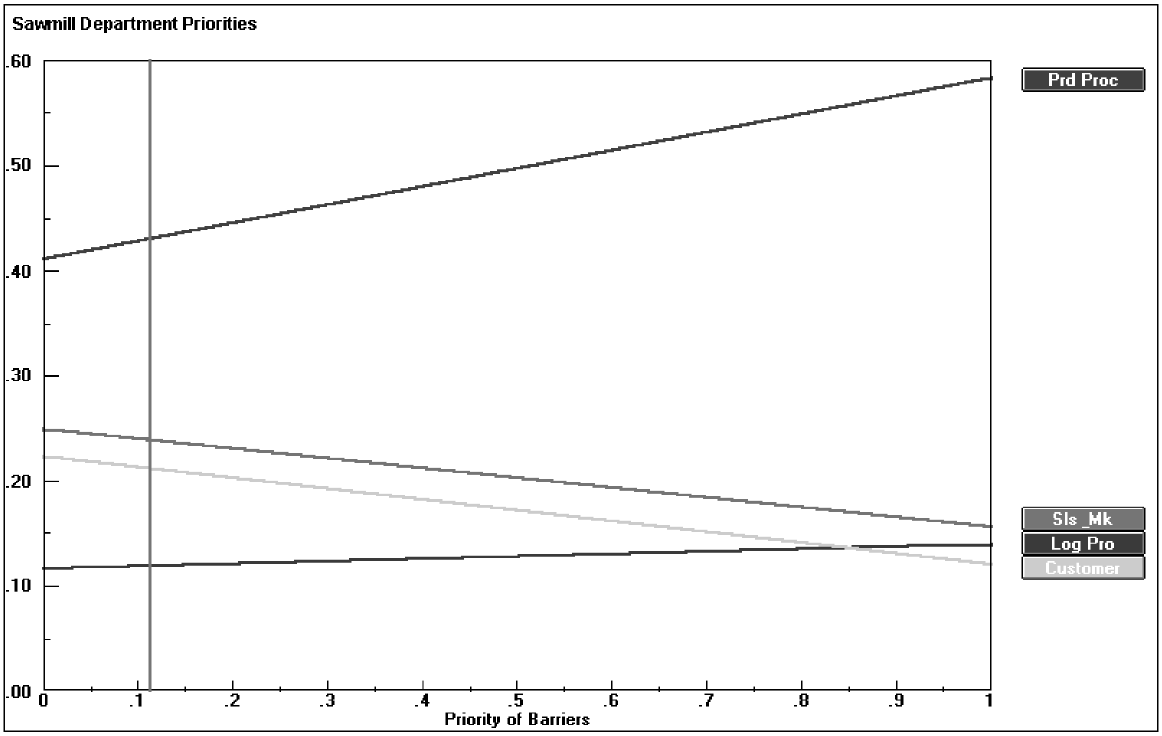

Figure 4-13: Adopter Sensitivity Analysis for Barriers

As the decision factor, *customer requirements*, becomes more important, the sales and marketing and the customer departments become more influential while the production process and the log procurement departments become less influential (Figure 4-14). At high importance levels of *customer requirements,* the influence of the production process department falls below the customer and the sales and marketing departments. If customer requirements are paramount in cases such as custom sorting or packaging, the production department becomes less influential. The large negative slope of the production process department may demonstrate the importance of the customer, despite the overall production emphasis.

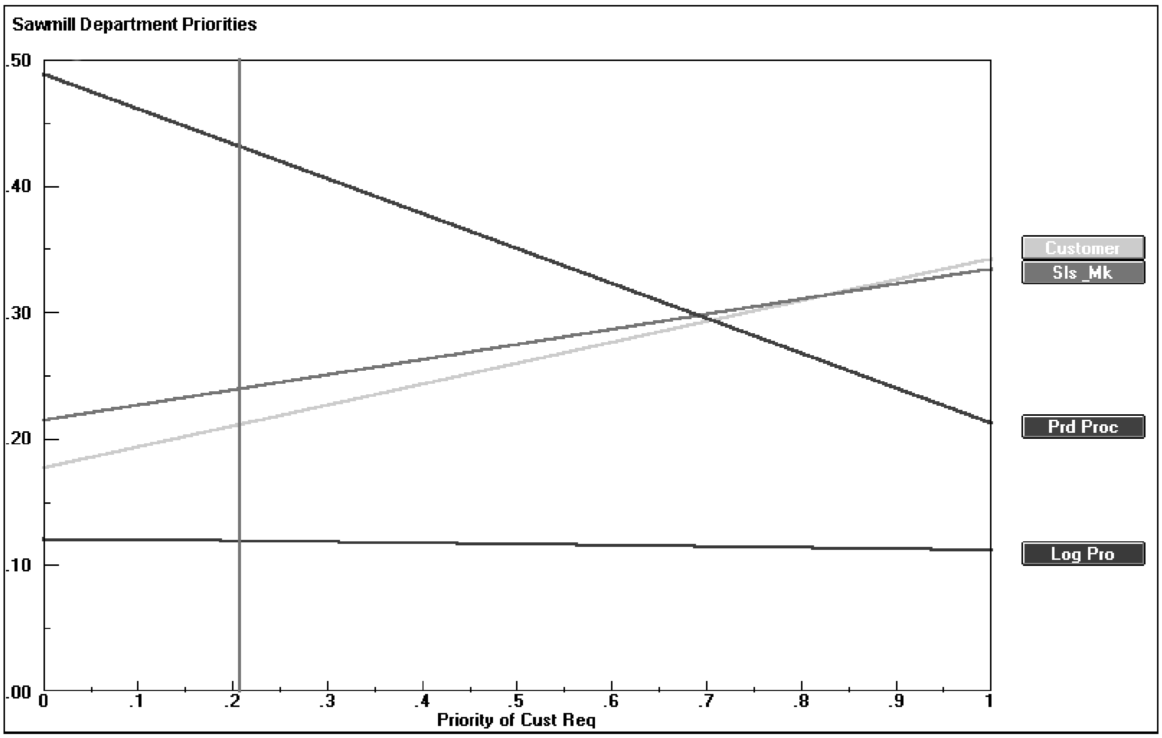

Figure 4-14: Adopter Sensitivity Analysis for Customer Requirements

Non-adopters

Figure 4-15 through Figure 4-20 graphically represent sensitivity analysis for the non-adopters group.

As the decision factor, *equipment features*, becomes more important, the production process and the log procurement departments become less influential while the sales and marketing and the customer departments become more influential (Figure 4-15). These results are very similar to the adopter group. If the equipment features of future scanning and optimizing technology allow a hardwood sawmill to better serve a customer's needs, the influence of these two departments becomes more important.

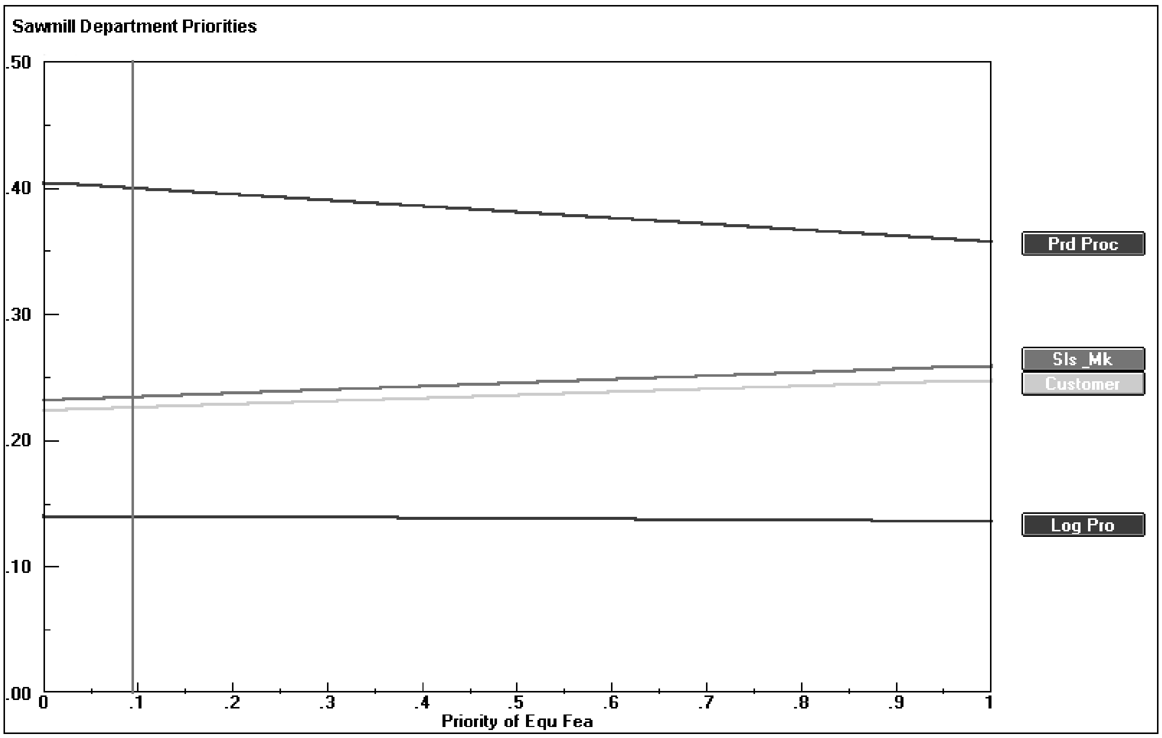

Figure 4-15: Non-adopter Sensitivity Analysis for Equipment Features

As the decision factor, *production improvements*, becomes more important, the production process and the customer departments become less influential while the sales and marketing and the log procurement departments become more influential (Figure 4-16). However, the line slopes are very small. Non-adopters perceive that both the sales and marketing and the log procurement departments play a larger role if production increases.

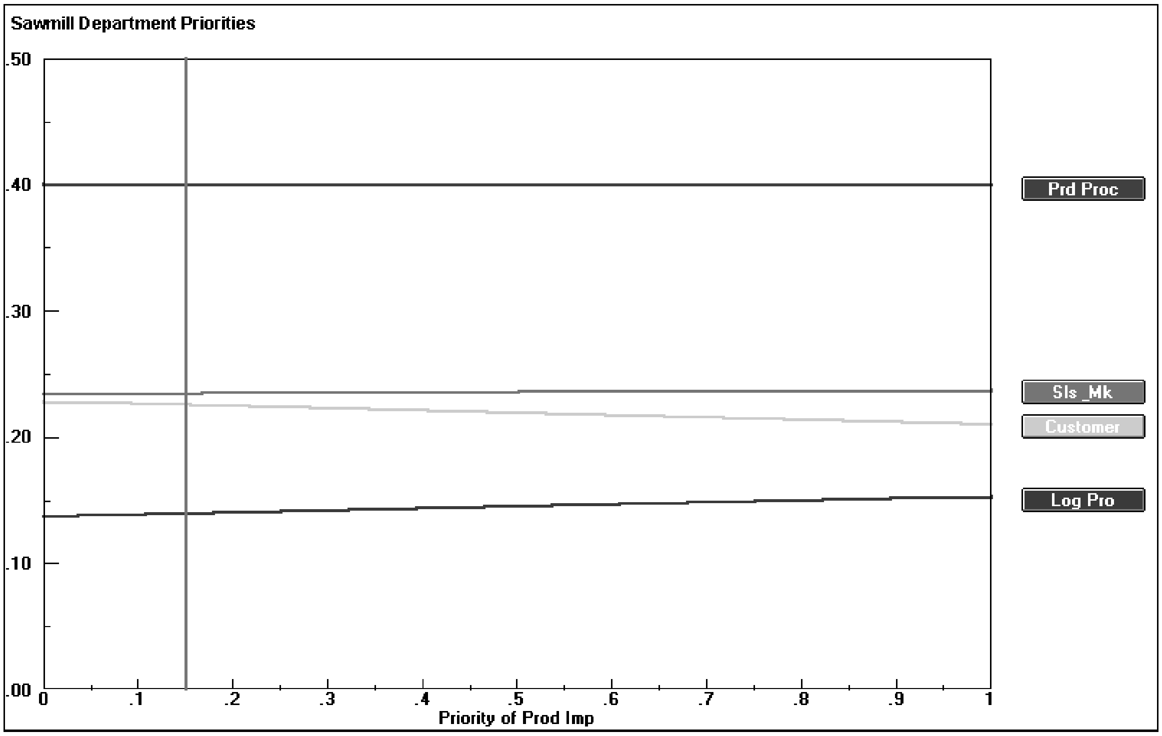

Figure 4-16: Non-adopter Sensitivity Analysis for Production Improvements

As the decision factor, *mill communications*, becomes more important, the production process and the customer departments become less influential while the sales and marketing and the log procurement departments become more influential (Figure 4-17). Small sloped departmental influence lines indicate little change.

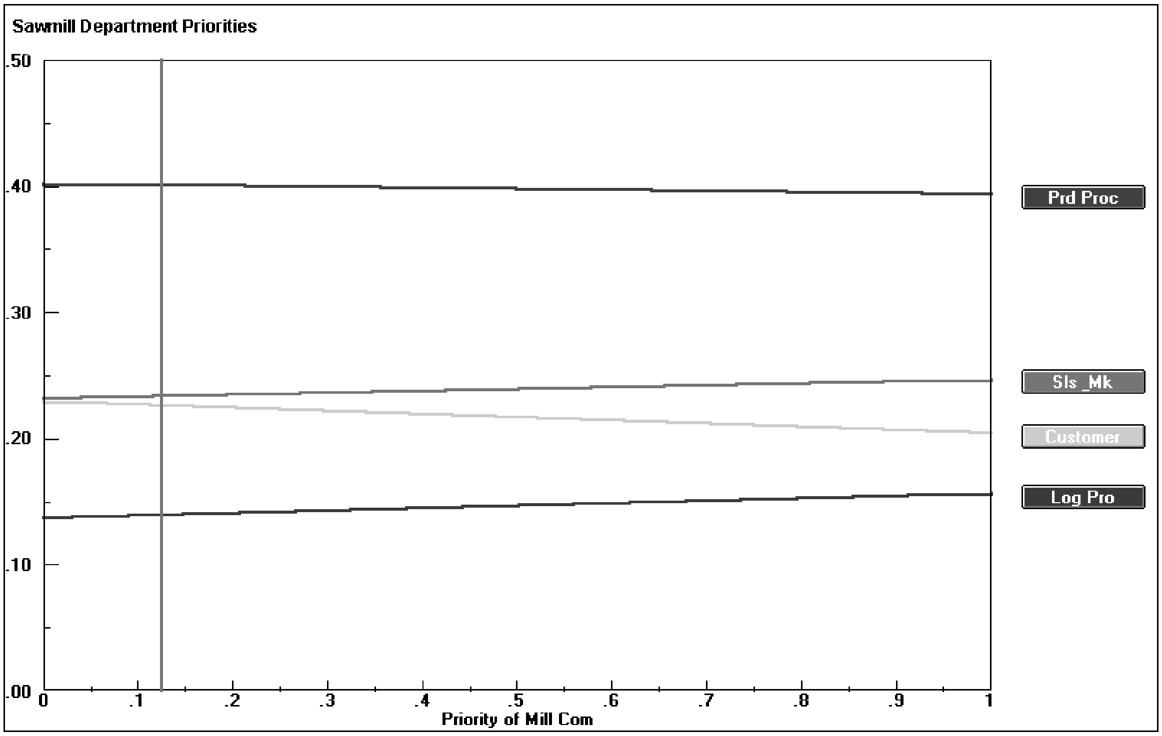

Figure 4-17: Non-adopter Sensitivity Analysis for Mill Communications

As the decision factor, *maintenance issues*, becomes more important, the sales and marketing and the customer departments become less influential while the production process and the log procurement departments become more influential (Figure 4-18). The slope of the production process department is high. High production during uptime may be critical if maintenance issues are a problem.

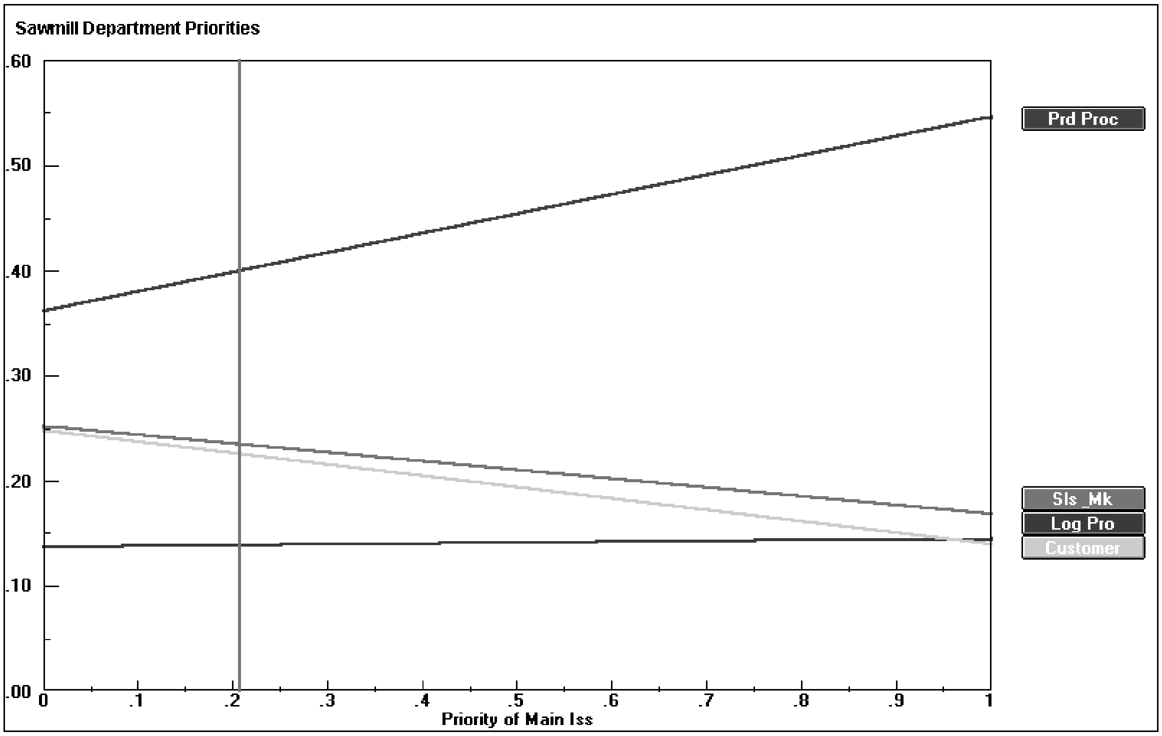

Figure 4-18: Non-adopter Sensitivity Analysis for Maintenance Issues

As the decision factor, *barriers*, becomes more important, the sales and marketing and the customer departments become less influential while the production process and the log procurement departments become more influential (Figure 4-19). If barriers such as initial cost become more important, the respondents may have seen increases in production as a way of offsetting this barrier.

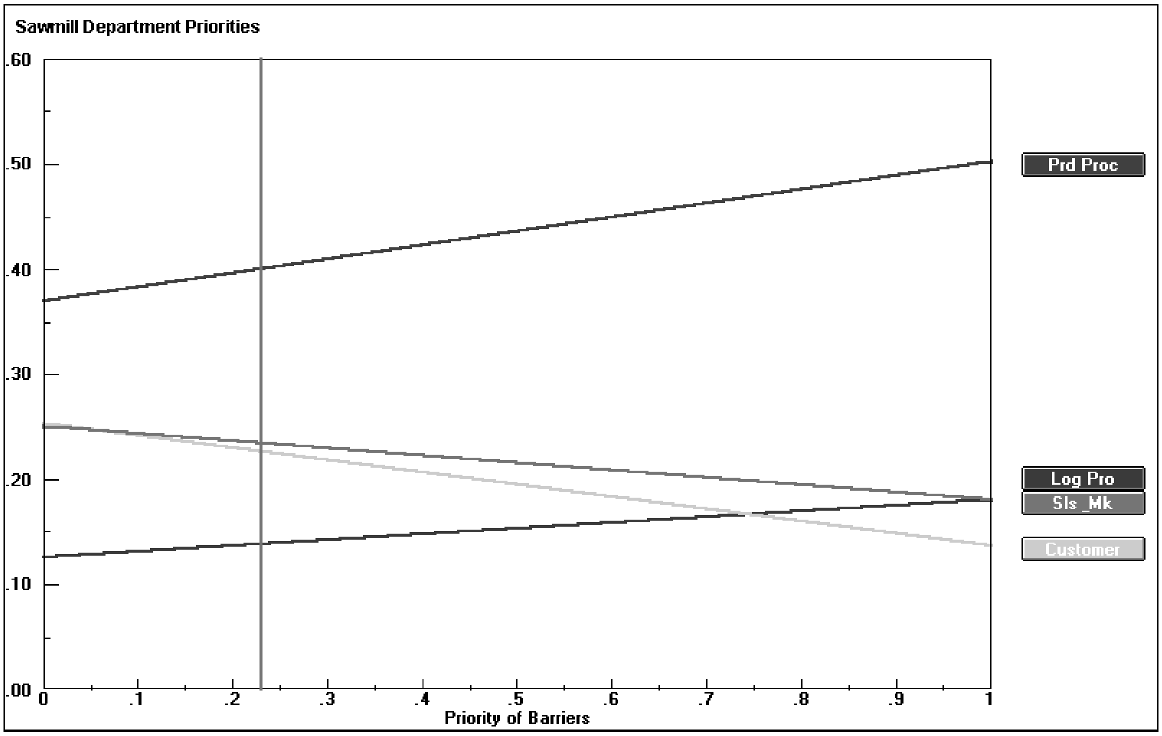

Figure 4-19: Non-adopter Sensitivity Analysis for Barriers

As the decision factor, *customer requirements*, becomes more important, the sales and marketing and the customer departments become more influential while the production process and the log procurement departments become less influential (Figure 4-20). These results are similar to the adopter model. If customer requirements are paramount in cases such as custom sorting or packaging, the production department becomes less influential, and the customer's needs (influence) surpasses the production department.

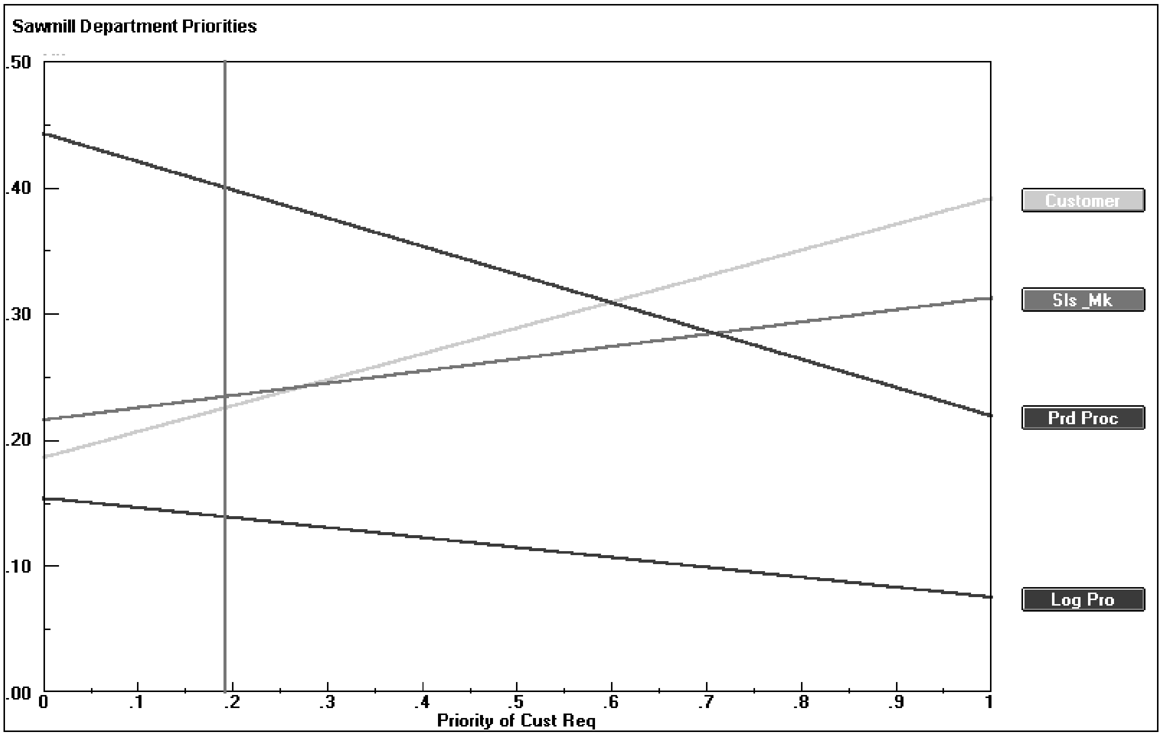

Figure 4-20: Non-adopter Sensitivity Analysis for Customer Requirements

Preliminary Interview Questions

Preliminary questions were asked at the beginning of the interview process to put the interviewee at ease and to generate a relaxed atmosphere. Their responses further validated the data gathered in the mail survey.

When asked if they believed that scanning and optimizing technology would benefit their sawmill, all but one adopter said yes. The remaining adopter stated that it was difficult to determine given the other consecutive improvements made at the mill. Nine of the non-adopters said yes with 4 stating that they would need to study the payback in more detail. Three non-adopters felt that their company was too small to consider such technology.

All of the adopters agreed that there was accurate and truthful information available on scanning and optimizing technology; however, most agreed that it was often exaggerated. Nine of the non-adopters believed that it was accurate and truthful to a degree. The remaining non-adopters said that they would need to see the technology operate in person.

When asked what negative things they have heard about scanning and optimizing technology, the adopters listed maintenance and technical support problems, reliability, and training issues. Non-adopters also listed maintenance issues. Four stated that initial cost was a barrier. Others commented that they haven't heard about or did not know a great deal about this technology.

When asked about specific features that scanning and optimizing technology would have to have before they would install it, adopters listed features such as complete defect identification, closer scan resolution, two sided scanning, statistical process control capabilities, and flexible programming. Non-adopters listed manual override, grading, accuracy, and speed features.

Finally, when asked if the decision to adopt scanning and optimizing technology was a group or an individual decision, 10 adopters stated it was a group and 1 stated it was an individual decision. Eleven non-adopters said it was a group decision with 4 stating it was an individual decision.

Conclusions

The AHP was an effective modeling tool for the hardwood sawmill industry. This model was chosen specifically for its ability to examine hardwood sawmills from a system perspective. A hardwood sawmill managed as a system would demonstrate interdepartmental cooperation where the sawmill is viewed as a whole, not as individual parts. An initial premise of this research was that those sawmills with advanced scanning and optimizing technology were more innovative and more inclined to manage their sawmills from a systems perspective. These sawmills would view log procurement, the production process, sales and marketing, and the customer more equally. In contrast, sawmills that had not adopted advanced scanning and optimizing technology were thought to be less innovative and less likely to manage from a systems perspective.

Two groups of hardwood sawmills were examined including adopters of and non-adopters of advanced scanning and optimizing technology. The adoption decision process for future scanning and optimizing technology was successfully examined for these two groups. First, the relative importance of key decision factors was identified. Second, the adoption decision influence of the four sawmill departments was identified. Finally, the fashion in which departmental influence changed was modeled by adjusting the relative importance of the decision factors.

Overall, the initial premise that adopters of advanced scanning and optimizing technology manage from a systems perspective was not found. When examining the influence of the four sawmill departments in the adoption decision process, adopters rated the *production process* over 2 times higher than the next highest department. Non-adopters also rated the *production process* the highest; however, the overall rating of the four departments' influence was more evenly distributed in the non-adopter model. The *log procurement*, *customer*, and *sales and marketing* departments were all rated higher by the non-adopters versus the adopters. This may demonstrate that systems thinking is more prevalent with the non-adopting group.

With respect to the decision factor ratings, adopters rated *production improvements* as the most important decision factor. This was followed by *customer requirements* and *maintenance issues*. In contrast, non-adopters rated *barriers* as the most important decision factor followed by *maintenance issues* and *customer requirements*. *Production improvements* was rated fourth by the non-adopters.

Overall, adopters rated production as the most important decision factor and sawmill department. Their general management philosophy could be described as a production orientation. The adoption of future scanning and optimizing technology by adopters will likely be done to satisfy a production objective. The *maintenance issues* decision factor was highly rated by both adopters and non-adopters. Chronic maintenance problems soon become production issues. The decision factor *customer requirements* was highly rated by both adopters and non-adopters. This may demonstrate that customer requirements are considered in the production process. This would be reasonable since they are the end user. In addition, the high rating of *customer requirements* validates the decision to include it as a decision factor. Finally, *barriers* was rated as the highest decision factor for non-adopters. Many of the non-adopters were small companies where the high initial cost of future scanning and optimizing technology would be prohibitive.

Sawmill management anatomy may have played a role in the outcome of the adopter and non-adopter models. The owners or managers of small hardwood sawmills (non-adopters) frequently perform many functions within the sawmill. They may procure logs, work in production, perform maintenance, and sell the final product. This wide-ranging job description would give them a systems view of the sawmill. This may explain the more evenly rated model. Mill managers of large sawmills (adopters) are often concerned only with the production process in a sawmill. This may explain the production orientation in the final model.

Sensitivity analysis was used to investigate the sensitivity of the sawmill departments to changes in the priorities of the decision factors. For both adopters and non-adopters, the *production process* was rated as the most influential department in the adoption decision process for future scanning and optimizing technology. This changes, however, as certain decision factors become more important. The *customer* and *marketing and sales* departments become more influential than the *production process* department when the *customer requirements* decision factor becomes large. This held true for both the adopter and non-adopter models. Any specialty or custom manufacturer may find a similar situation where customer requirements are more important than production levels. For both the adopters and non-adopters, the *customer* department eventually becomes the most influential department under the *customer requirements* decision factor. *Log procurement* was the least influential department for both adopters and non-adopters. It becomes more influential than the *customers* department, however, when the *barriers* decision factor becomes very important. Increased log procurement and increased production would be necessary to offset barriers such as high initial cost. In both the *barriers* and *maintenance issues* decision factors, the *production process* department becomes increasingly important for adopters and non-adopters. Barriers such as high initial cost or mill layout restrictions demand input from the *production process* department. High production or at least high lumber revenues would be needed to offset these obstacles. Maintenance issues also demand attention from the production department. Repair downtime and preventative maintenance downtime directly affect the production process.

In summary, the AHP model is an effective model to evaluate the hardwood sawmill industry from a system perspective. This research indicates that firms that have adopted currently available technology were more likely to be production oriented. In promoting future scanning and optimizing technology, high production firms and/or current technology-using firms should be targeted as early adopters. The users of current technology have already demonstrated their willingness to adopt a technology to improve their production. The large producing non-adopters could be persuaded to do so if the production benefits of this technology could be demonstrated. Paralleling the findings in the earlier chapters, barriers such as cost are important in the decision process. A significant segment of the hardwood sawmill industry will not consider such technology if cost barriers are not addressed. Future scanning and optimizing technology will address future production and renewable natural resource issues. Understanding how decisions are made within the hardwood sawmill industry will speed the adoption process.

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CHAPTER 5: Implications of Scanning and Optimizing Technology in the Hardwood Sawmill Industry

Research Summary

Three primary objectives were proposed at the beginning of this research project which included determining the differences between adopters and non-adopters of scanning and optimizing technology, identifying the company expectations of scanning and optimizing technology, and modeling the adoption decision process for future scanning and optimizing technology. These objectives were chosen because timely information was not available on the hardwood sawmill industry, and even less was known about the overall state of technology within the industry. Scanning and optimizing technology benefits hardwood sawmills by increasing its overall efficiency and revenues. The information generated from this research will help the manufacturers of scanning and optimizing technology address the concerns and expectations of the hardwood sawmill customer. In addition, university research and extension efforts in sawmill improvement and natural resource utilization can be directed by these findings. Ultimately, efforts by the technology manufacturers and university personnel to demonstrate the benefits of this technology will help the hardwood sawmill industry.

Industry Overview

This research provided a nationwide snapshot of the hardwood sawmill industry. The mail survey data was wide reaching providing information on company size and current technology use. Over half of the respondents were classified as large companies (20 or more employees) with a mean annual production of 11.7 million bdft. These high production levels indicate that there is a significant portion of medium and large hardwood sawmills in operation today. What was even more surprising was the lack of scanning and optimizing technology in use by hardwood sawmills. The most common type of scanning and optimizing technology, headrig optimization, was only in use by 27 percent of the responding mills. Advanced scanning and optimizing technology such as edger-optimizers and trimmer-optimizers were only in use by 10 percent and 5 percent of the respondents respectively. The number of medium and large hardwood sawmills in combination with the lack of existing technology suggests that there is a large market potential for scanning and optimizing technology in the hardwood sawmill industry if this technology is promoted properly.

If scanning and optimizing technology will improve a sawmill's revenues, why don't more sawmills adopt this technology? One reason that has been examined is the high initial cost of this technology. There will be a segment of the hardwood sawmill population that will not be able to afford this technology (small sawmills). Another possible reason is that sawmills do not see the need for this technology. One of the most common statements encountered during the mill visits was that the price for logs is steadily increasing. Scanning and optimizing technology may provide the necessary margin increases to remain competitive and profitable. Finally, other sawmills may have not adopted scanning and optimizing technology because of a lack of or erroneous information on this technology. This information issue could be addressed directly by the equipment manufacturers. Data collected on information sources showed that plant visits and peer conversations were the two most highly rated information sources for scanning and optimizing technology. Manufacturers could organize meetings or social events that incorporate mill tours and personal input from technology adopters. In addition, association meetings and symposiums were highly rated information sources. Regional meetings targeted at the hardwood sawmill (not the researcher) could offer another opportunity for manufacturers to demonstrate the benefits of this technology. Finally, the Internet was rated last as an information source. These findings were similar to other wood products industry studies from the early 1990s. The Internet is not the best medium for the promotion of scanning and optimizing technology in the hardwood sawmill.

Advanced & Future Scanning and Optimizing Technology

The research examined current edger-optimizers, future edger-optimizers, and future automated grading systems within the hardwood sawmill industry. The results made it clear that production related issues were the most important decision factors for advanced scanning and optimizing technologies. Recall that for a current edger-optimizer, improved raw material recovery and increased lumber revenues were the two most highly rated factors. These were also the two most frequently selected decision factors from the future edger-optimizer data. It is also important to note that initial cost was also highly rated for both current and future edger-optimizer technologies.

The data collected on future automated grading systems also showed a production trend with accuracy of grading rated the highest. Accuracy of grade is a revenue issue which many sawmillers equate with production. Other highly rated factors dealt with system durability and lifespan. This likely demonstrated the respondent's concerns of a high-tech system operating successfully in the harsh sawmill environment. As with the earlier systems, initial cost was also highly rated. These results show the importance of proving such technology before it will be readily accepted by the hardwood sawmill industry.

Several comparisons were made for current edger-optimizers and future automated grading systems. Comparisons were performed for several groups including large versus small companies, technology adopter versus technology non-adopter companies, and NHLA member versus non-NHLA member companies. It was found that large companies, technology adopters, and NHLA members rated very similarly. Likewise, small companies, technology non-adopters, and non-NHLA members rated very similarly.

Contrary to our original premise, production issues were rated significantly higher by companies that have advanced scanning and optimizing technology as compared to companies that did not. Initially, it was proposed that companies that have adopted advanced scanning and optimizing technology were more innovative and likely viewed their sawmill from a systems perspective. From a systems perspective, they would view the different sawmill departments as interrelated and equally important. The fact that production factors rated at the top suggest that the systems perspective is weighted heavier on the production side. Other comparisons showed that large companies rated vendor support significantly higher. Since large companies are a primary market for scanning and optimizing technology, manufacturers of this technology must stress service and support as a part of their total product.

Comparisons between groups for the future automated grading systems also supported earlier findings. Production issues such as speed and service issues such as training from vendor were rated significantly higher by large companies versus small companies. Small companies rated initial cost significantly higher. Similar results were reported for the other comparison groups. These comparisons show that production issues are important for the large target mills, training and service is important for new technologies, and cost will be a barrier for many companies.

Modeling the Adoption Decision Process

Finally, the adoption decision process for future scanning and optimizing technology was modeled. Two groups, including adopters and non-adopters of advanced scanning and optimizing technology, were included. The AHP model was used to identify important decision factors in the adoption decision process for future scanning and optimizing technology. This model also allowed us to examine the hardwood sawmill from a systems perspective by weighting how much influence each sawmill department had on the adoption decision process.

The initial analysis from the mail survey results showed that production issues were most important for the technology adopters. This was contrary to our initial premise that technology adopters were more innovative and likely viewed the sawmill from a systems perspective. The AHP model further supported the mail survey results by weighting the adopters' production improvement decision factor the highest and nearly twice as high as the non-adopters. The barriers decision factor was the highest weighted decision factor for the non-adopter and over twice as great as the adopter weighting. This further supports that barriers such as initial cost will be significant obstacles for small hardwood sawmills.

Overall and contrary to our initial premise, the non-adopters weighted all of the decision factors more evenly than the adopters. This suggests that a systems perspective may be more prevalent with the non-adopters versus the adopters. This result is supported by the anatomy of the non-adopter sawmill. The owners or managers of the small operation often serve multiple roles such as log buyer, production manager, and lumber manager. This broad exposure would give these individuals an understanding of the importance each department.

The model further examined this systems perspective by weighting the influence that the different sawmill departments have on the adoption decision process for future scanning and optimizing technology. Again, the production process department was weighted higher in the adopter model. Overall, the non-adopters rated the log procurement, the customer, and the sales and marketing departments higher. This provides further evidence of a systems perspective with non-adopters.

The AHP model has the capability to perform sensitivity analysis. This allowed us to see how the influence of the various departments changed as the various decision factors became more or less important. Overall, the production process was the highest rated sawmill department for both the adopters and non-adopters. The production process showed sharp increases in importance as maintenance issues and barriers became more important for both the adopter and the non-adopter groups. Manufacturers of this technology must demonstrate the durability of this technology. If the production department does not believe in the durability of scanning and optimizing technology, their influence may weight against technology adoption. The production process department's influence increases as barriers becomes more important. This further supports earlier findings. Companies see higher production as necessary to offset the high cost issues of scanning and optimizing technology. Manufacturers should stress that increased production may not be the result or needed result of this technology. Improved raw material utilization and board upgrade are the two most important benefits. Improved raw material recovery offsets increasing log prices and competition between sawmills to purchase logs, and board upgrade generates more revenue from the same number of boards without increasing demand for logs and finding new markets for higher production volumes.

The sensitivity analysis also generated scenarios where the influence of the production department fell below the influence of other departments for both adopters and non-adopters. In situations where the customer requirements decision factor became more important, the influence of the customer and the sales and marketing departments became more important in the adoption decision process for future scanning and optimizing technology. This technology will have the ability to produce lumber under any number of programmed parameters. Given its ability to identify all defect information, very specific parameters could be programmed to fit the customer's needs. This would fit the custom and specialty markets. It could also apply to a close and integrated customer / supplier relationship.

Overall, the results of the model were supported by the earlier mail survey findings. This overlap validates the choice of the AHP model and generated new information for the forest products scientific base.

Study Limitations

The scattered nature of the hardwood sawmill industry made it difficult to identify all of the hardwood sawmills in the United States. Many of the sawmills that went unidentified were likely very small and would not seriously consider scanning and optimizing technology. It was not our intention to identify every small and hobby mill; however, our sampling method provided an accurate representation of the industry. Given the consolidation trends in the hardwood sawmill industry, the total hardwood sawmill population will likely continue to decline.

The AHP modeling portion of this research was based on a limited number of personal interviews. The number of personal interviews was limited by several factors including availability and cost. The adopters of advanced scanning and optimizing technology were few in number. Seven states had to be included to find 11 adopters. In addition, further interviews were limited by travel expenses. The limited number of interviews is not uncommon for case study research. The final model results were validated by the complimentary findings in the mail survey. Replication of this study would further validate the use of the AHP model.

It also would have been useful to incorporate return on investment (ROI) into the mail survey. This concept was eluded to with the cost issues that were examined; however, ROI would have provided more informational depth than cost-only information.

Finally, the personal interviews were conducted with the primary decision-makers. It was up to this individual to consider the input of the other management personnel when answering the model questions. Multiple decision-maker input would be another possibility for the AHP model, but interview logistics would be a challenge and the sample size would likely be reduced.

Perspective of the Hardwood Sawmill Industry

The information from the mail survey, the AHP model, and interaction with hardwood sawmills during the research process have influenced my perceptions of the hardwood sawmill industry. I believe that scanning and optimizing technology will play larger role within the industry in the future. The marketing efforts of the technology manufacturers will determine the rate of scanning and optimizing technology adoption by the industry. Several observations from the hardwood sawmill industry deserve mention.

First, economics drive technology adoption. Current technology adopters installed scanning and optimizing technology to improve their production. The ultimate goal was to increase revenues based on increased production. Technology manufacturers must promote the sound economic feasibility of this technology. Initial cost will be a barrier for many companies; however, medium and large producers could be persuaded to adopt if the return on investment is clearly demonstrated.

Second, much of the current hardwood sawmill industry can be described as a commodity market. Hardwood sawmills are price takers. Because of this, sawmills must optimize margins and increase efficiencies to lower costs. Scanning and optimizing technology can help hardwood sawmills achieve these objectives.

Third, scanning and optimizing technology would help to improve a sawmill's competitive position. Increases in quality and consistency will better serve the customers' needs. Specific attention to a customers' needs will move a sawmill away from the price-takers position to a price-makers position. This was demonstrated by the sensitivity analysis where the customer and the sales and marketing departments became more influential as customer requirements become more important.

Fourth, future scanning and optimizing technology will do much more than edge and grade hardwood lumber. The ability to identify all defects will allow sawmills to produce very specific products based upon their customers' *needs*. Systems thinking will be necessary to achieve the full potential of future scanning and optimizing technology.

Fifth, a great deal of value can be added to a board if all of the defects and cutting units are identified. A sawmill’s role could be reduced to primary log breakdown with defect detection and bar coding. The customer, such as a dimension mill, would then use the bar code information to optimally utilize the board. A sawmill’s role could also expand with this technology by vertically integrating into dimension manufacturing. Cutting dimension parts before kiln drying could improve kiln capacity and efficiency. This technology is already used in German production facilities. These activities would further move the hardwood sawmill industry away from the price-takers position.

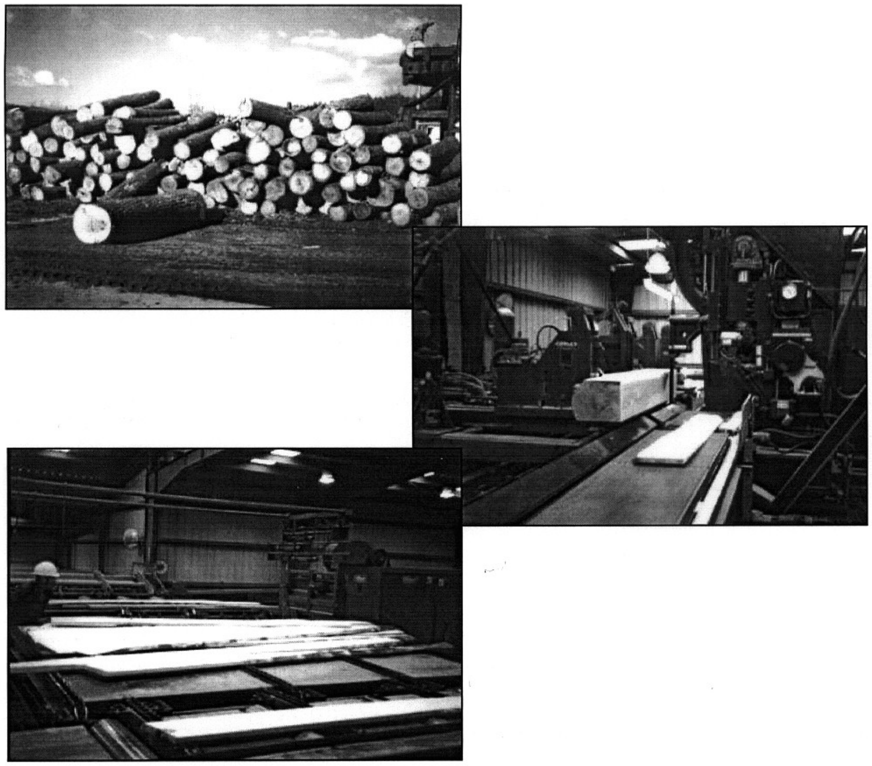
Finally, the hardwood sawmill industry must grasp the full meaning of *optimization*. Currently, the industry has a limited view of optimization which focuses on increasing production recovery. This definition is expanded by current scanning and optimizing technology such as edger-optimizers to include improved value recovery. Even this view is restricted. To be fully optimized, the hardwood sawmills must view their industry from a systems perspective. All parts of the sawmill and its customers must be considered for future success.

Future Research

The logical path for future research on scanning and optimizing technology in the hardwood sawmill industry would include successful field testing of prototype machines such as the AutoGrade system. This would demonstrate the current capabilities of the system and identify areas for improvement. It would also be beneficial to further investigate the management philosophies of the hardwood sawmill. This research has demonstrated the production philosophy of hardwood sawmills. Research and extension efforts could focus on the adoption of the systems approach in hardwood sawmill management.

APPENDIX A: Mail Survey

HARDWOOD LUMBER SCANNING AND OPTIMIZING TECHNOLOGY



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Virginia Tech
VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY

Questionnaire: Cover

HARDWOOD LUMBER SCANNING AND OPTIMIZING TECHNOLOGY

Virginia Tech is examining technology in the hardwood lumber industry. Future development of hardwood sawmill technology will improve the efficiency of the hardwood sawmill. The information generated from this survey will help sawmill managers make more informed decisions, as well as improve hardwood lumber scanning and optimizing technology. Hardwood lumber scanning and optimizing technology refers to existing **edger-optimizers**, future **more advanced edger-optimizers**, and emerging **automated lumber grading systems**. This information is critical for moving hardwood sawmill technology in the proper direction. Please take a few minutes to answer the following questions. Thank you for your time and valuable input.

1. Does your sawmill manufacture hardwood lumber?

☐ No ⋗ Stop. Please fold with return address showing; return questionnaire

☐ Yes ⋗ Please Continue

2. Is your sawmill part of a multiple facility company with more than one production facility or is your sawmill a single operation?

☐ Part of a multiple facility company
☐ Single operation

3. What is the total number of employees at your sawmill? (single facility number not the corporate or multiple facility number)

____________Number of Employees

4. Does your sawmill perform any of the following value added processes? (check all that apply)

☐ Air Drying
☐ Kiln Drying
☐ Surfacing
☐ NHLA Grading
☐ Custom Grading
☐ Custom Sorting
☐ End Coating
☐ Dimension Manufacturing
☐ Other (please specify)___________________

5. Does your sawmill have any type of scanning or optimizing technology? (check all that apply)

☐ Bucking-optimizer
☐ Headrig-optimizer
☐ Edger-optimizer
☐ Grade Mark Reader
☐ Trimmer-optimizer
☐ Automated Sorting
☐ Other (please specify)___________________
☐ None

6. Please estimate the total volume of <u>hardwood lumber</u> your sawmill produced in 1998.
(single facility volume not the corporate or multiple facility volume)

________________________ board feet

7. Which species of <u>hardwood lumber</u> does your sawmill produce? (please indicate the percentage of total board feet that is in each species)

____________ % Red Oak
____________ % White Oak
____________ % Yellow-Poplar
____________ % Hard Maple
____________ % Soft Maple
____________ % Black Cherry
____________ % Black Walnut
____________ % Ash
____________ % Red Alder
____________ % Aspen or Cottonwood
____________ % Other hardwoods (please specify) ________________

Total = 100%

Questionnaire: Page 1

Currently, commercial edger-optimizer systems exist that use scanning and optimizing technology to edge lumber in the hardwood sawmill. We are interested in feedback from both sawmills that have this technology and sawmills that do not have this technology. Please consider the following questions about edger-optimizers.

8. Please rate the importance of the following factors when deciding to adopt an edger-optimizer system.

	Least Important			**Average Importance**			**Most Important**
Initial Cost	1	2	3	4	5	6	7
Training of New Operators	1	2	3	4	5	6	7
Operational Costs	1	2	3	4	5	6	7
Installation Down Time	1	2	3	4	5	6	7
Maintenance Costs	1	2	3	4	5	6	7
Improved Raw Material Recovery	1	2	3	4	5	6	7
Increased Production Levels	1	2	3	4	5	6	7
Increased Lumber Revenues	1	2	3	4	5	6	7
New Mill Installation	1	2	3	4	5	6	7
Existing Mill Layout Restrictions	1	2	3	4	5	6	7
Advice From Sales Department	1	2	3	4	5	6	7
Improved Lumber Quality	1	2	3	4	5	6	7
Advice From Customers	1	2	3	4	5	6	7
Improved Lumber Consistency	1	2	3	4	5	6	7
Advice From Production Supervisors	1	2	3	4	5	6	7
Training from Vendor	1	2	3	4	5	6	7
Ease of Use	1	2	3	4	5	6	7
Availability of Vendor Support	1	2	3	4	5	6	7
Ability to Upgrade	1	2	3	4	5	6	7
System Lifespan	1	2	3	4	5	6	7

9. What would you be willing to pay for an edger-optimizer?

(including the scanners, computers, and edger; not the material handling system)

- ☐ Less than $100,000
- ☐ $100,001 - $250,000
- ☐ $250,001 - $500,000
- ☐ $500,001 - $1,000,000
- ☐ Greater than $1,000,000

Questionnaire: Page 2

Current commercially available edger-optimizers base their decisions on size and wane information only. Advanced edger-optimizers are being developed that base their decisions on more information. These systems will optimize based on NHLA grading rules using surface defect information in addition to size and wane information. Please consider the following questions regarding future more advanced edger-optimizers.

10. **For you to purchase an upcoming more advanced edger-optimizer system based on NHLA grading rules, what features or abilities would this system need to have?** (check all that apply)

- ☐ Improved Raw Material Recovery
- ☐ Increased Production Levels
- ☐ Increased Lumber Revenues
- ☐ Training from Vendor
- ☐ Ease of Use
- ☐ Reliability
- ☐ Maintenance Costs
- ☐ Availability of Vendor Support
- ☐ Flexible Grade Programming
- ☐ Product Consistency
- ☐ Initial Costs

11. **Would you consider installing upcoming more advanced edger-optimizer systems using NHLA grading rules?**

- ☐ No
- ☐ Yes

If Yes, what would you be willing to pay for an upcoming more advanced edger-optimizer systems based on NHLA grading rules? (including the scanners, computers, and edger; not the material handling system)

- ☐ Less than $100,000
- ☐ $100,001 - $250,000
- ☐ $250,001 - $500,000
- ☐ $500,001 - $1,000,000
- ☐ Greater than $1,000,000

12. **What is your expected payback, in years, for this technology?**

________________________ Years

13. **Please check the <u>one</u> category that best reflects your sawmill's hourly hardwood lumber production volume.** (single facility volume not the corporate or multiple facility volume)

- ☐ 0 - 1000 board feet per hour
- ☐ 1001 - 2000 board feet per hour
- ☐ 2001 - 3000 board feet per hour
- ☐ 3001 - 4000 board feet per hour
- ☐ 4001 - 5000 board feet per hour
- ☐ 5001 - 6000 board feet per hour
- ☐ 6001 - 7000 board feet per hour
- ☐ Greater than 7000 board feet per hour

14. **How many shifts does your sawmill work each day?** (single facility number not the corporate or multiple facility number)

- ☐ 1 shift
- ☐ 2 shifts
- ☐ 3 shifts

15. **What is the <u>average</u> shift length at your sawmill?**

________________________ Hours

Questionnaire: Page 3

Currently, systems are being developed that automatically grade hardwood lumber without a human operator. Please consider the following questions regarding future automated lumber grading systems.

16. Please rate the importance of the following factors for adopting future automated hardwood lumber grading systems?

	Least Important			Average Importance			Most Important
Accuracy of Grading	1	2	3	4	5	6	7
Initial Cost	1	2	3	4	5	6	7
Durability	1	2	3	4	5	6	7
Compatibility with Existing Equipment	1	2	3	4	5	6	7
Speed	1	2	3	4	5	6	7
Ability to Quickly Switch Species	1	2	3	4	5	6	7
Ability to Modify NHLA Grading Rules	1	2	3	4	5	6	7
Simplicity of Operation	1	2	3	4	5	6	7
Training of New Operators	1	2	3	4	5	6	7
Equipment Warranty	1	2	3	4	5	6	7
Reduction of Grading Costs	1	2	3	4	5	6	7
Tallying Capabilities	1	2	3	4	5	6	7
Sorting Capabilities	1	2	3	4	5	6	7
Color Sorting Capabilities	1	2	3	4	5	6	7
Ease of Use	1	2	3	4	5	6	7
Availability of Vendor Support	1	2	3	4	5	6	7
Ability to Upgrade	1	2	3	4	5	6	7
System Lifespan	1	2	3	4	5	6	7
NHLA Grading Rules	1	2	3	4	5	6	7
Training from Vendor	1	2	3	4	5	6	7

17. What would you be willing to pay for an automated grading system?
(including the scanners and computers; not the material handling system)

- ☐ Less than $100,000
- ☐ $100,001 - $250,000
- ☐ $250,001 - $500,000
- ☐ $500,001 - $1,000,000
- ☐ Greater than $1,000,000

Questionnaire: Page 4

18. **Please mark the category which best describes your position within the sawmill.**

☐ Owner
☐ Upper Management
☐ Middle Management
☐ Other (please specify)___________________

19. **Please check the box that most closely reflects your level of education.**

☐ High School
☐ Two-year College
☐ Four-year College
☐ Graduate School
☐ Other (please specify)___________________

20. **Please check the box that most closely reflects your age.**

☐ Under 29
☐ 30-39
☐ 40-49
☐ 50-59
☐ 60 years and older

21. **When deciding to install scanning and optimizing technology, is this an individual decision (manager or owner) or group decision (management and plant staff)?**

☐ Individual
☐ Group

22. **Do you believe that scanning and optimizing technology would benefit your sawmill?**

☐ No
☐ Yes
Please Explain:

23. **The complete sawmill can be broken into four basic components including *Raw Material Procurement, the Production Process*, *Sales and Marketing*, and *the Customer.* This complete sawmill can be called the *Sawmill System*. How important are each of these components when adopting new sawmill technology?**

	Least Important			Average Importance			Most Important
Raw Material Procurement	1	2	3	4	5	6	7
Production Process	1	2	3	4	5	6	7
Sales and Marketing	1	2	3	4	5	6	7
Customer	1	2	3	4	5	6	7

24. **Concerning hardwood lumber scanning and optimizing technology, rate the following sources of information as to their value to you.**

	Least Important			Average Importance			Most Important
Plant Visits	1	2	3	4	5	6	7
Manufacturer's Ads and Literature	1	2	3	4	5	6	7
Personal Sales Calls from Manufacturers	1	2	3	4	5	6	7
Meetings & Symposiums	1	2	3	4	5	6	7
Trade Journals	1	2	3	4	5	6	7
Scientific Journals	1	2	3	4	5	6	7
Peer Conversations	1	2	3	4	5	6	7
Unsolicited Sales Literature	1	2	3	4	5	6	7
Internet	1	2	3	4	5	6	7
Short Courses	1	2	3	4	5	6	7
News Letters	1	2	3	4	5	6	7
University Extension Personnel	1	2	3	4	5	6	7
Association Meetings	1	2	3	4	5	6	7
Consultants	1	2	3	4	5	6	7
Other	1	2	3	4	5	6	7

(please specify) ____________________________

Questionnaire: Page 5

25. Do you believe there is accurate and truthful information available on hardwood lumber scanning and optimizing technology?

- ☐ No
- ☐ Yes

26. Does your sawmill have a mission statement?

- ☐ No
- ☐ Yes

27. What were your sawmill's total hardwood lumber sales in 1998? (Single facility number not the corporate or multiple facility number.)

Total 1998 Sales: $___________________________

28. Please list the trade associations or professional associations that you belong to.

____
____
____

29. How many trade association or professional association business meetings do you attend each year?

__________ number per year

30. What negative things have you heard about hardwood lumber scanning and optimizing technology?

1)

2)

31. What specific features would an edger-optimizer, trimmer-optimizer, or automated grading system need to have before you would install it in your sawmill?

32. If we have missed any concerns of yours, please indicate them below. Please feel free to comment on hardwood sawmills, hardwood lumber scanning and optimizing equipment, or other issues.

Thank you for your help! Please fold along the dotted line shown on the next page, tape or staple, and return the questionnaire by mail. **The postage is prepaid.**

Questionnaire: Page 6

NO POSTAGE
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IN THE
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BUSINESS REPLY MAIL

FIRST-CLASS MAIL PERMIT NO. 10 BLACKSBURG, VA

POSTAGE WILL BE PAID BY ADDRESSEE

VIRGINIA TECH
THOMAS M. BROOKS FOREST PRODUCTS CENTER
ATTN: SCOTT BOWE
PO BOX 850
BLACKSBURG VA 24063-9985

Please return the questionnaire after folding in half and taping the ends together. Before mailing, please make sure that the return address is visible. The postage is prepaid.

VT/0023/0899/4M/200922

Questionnaire: Back Cover

Virginia Tech

CENTER FOR FOREST PRODUCTS
MARKETING AND MANAGEMENT

VIRGINIA POLYTECHNIC INSTITUTE
AND STATE UNIVERSITY

Scott Bowe
Department of Wood Science and Forest Products
1650 Ramble Rd., mail code 0503
Blacksburg, Virginia 24061
Phone: (540) 231-5876 Fax: (540) 231-8868
http://www.vtwood.forprod.vt.edu/cfpmm/
sbowe@vt.edu

September 3rd, 1999

Jacob Leinenkugel Brewing Co
Attn: Jacob Leinenkugel
1 Jefferson Avenue
Chippewa Falls, WI 54729

Dear Mr. Leinenkugel,

Future developments in hardwood sawmill technology will improve the efficiency of sawmills. New technologies are being developed which will improve the quality of hardwood lumber and increase profits. Virginia Tech is examining scanning and optimizing technology in hardwood sawmills. Hardwood lumber scanning and optimizing technology refers to existing edger-optimizers, more advanced edger-optimizers, and emerging automated lumber grading systems.
The information generated from this project will help sawmill managers make more informed decisions, as well as improve hardwood lumber scanning and optimizing technology. This information is critical for moving hardwood sawmill technology in the proper direction, which will ultimately increase your profits.

Your company was chosen at random from a list of hardwood sawmills. We are asking for you to help by completing and returning the enclosed questionnaire. The postage is prepaid. Since the number of participants is small, your response is vital for the success of this project.

Please be assured that your response will be treated with complete confidentiality. Your name and company will never be used in the study results. Only aggregated results will be reported. The questionnaire is numbered to allow me to remove your name from the mailing list when I receive your response. This will prevent future mailings to your company.

Thank you very much for your time and assistance. If you have any questions or comments, please feel free to contact me at 540-231-5876 (Phone), 540-231-8868 (Fax), or sbowe@vt.edu (Email).

Sincerely,

Scott Bowe
Graduate Student

A Land-Grant University - The Commonwealth Is Our Campus

First Cover Letter

Dear Hardwood Sawmill Manager,

We need your Help! Two weeks ago I mailed you a copy of a questionnaire titled **"Hardwood Lumber Scanning and Optimizing Technology."** I am contacting you to ask you to complete the questionnaire. If you have completed and returned it, please accept my sincere appreciation. The information generated from this survey will help sawmill managers make more informed decisions, as well as improve hardwood lumber scanning and optimizing technology. If you have not completed the questionnaire, please take a few minutes to fill it out and return it.

Since your name was chosen at random, your participation is critical for the success of the study. The information that you provide will be kept **strictly confidential**. The number on the questionnaire allows us to remove your name from future mailings. If you have any questions, please contact me at 540-231-5876. Our fax number is 540-231-8868. Thank you in advance for your participation.

Sincerely,

Scott Bowe
Graduate Research Assistant
Virginia Tech

Reminder Post Card

Virginia Tech

CENTER FOR FOREST PRODUCTS
MARKETING AND MANAGEMENT

VIRGINIA POLYTECHNIC INSTITUTE
AND STATE UNIVERSITY

Scott Bowe
Department of Wood Science and Forest Products
1650 Ramble Rd., mail code 0503
Blacksburg, Virginia 24061
Phone: (540) 231-5876 Fax: (540) 231-8868
http://www.vtwood.forprod.vt.edu/cfpmm/
sbowe@vt.edu

October 4th, 1999

Jacob Leinenkugel Brewing Co
Attn: Jacob Leinenkugel
1 Jefferson Avenue
Chippewa Falls, WI 54729

Dear Mr. Leinenkugel,

HELP!! In early September, I asked for your assistance with a hardwood lumber scanning and optimizing study. This information is vital for me to complete my project and graduate next May. Please take a few minutes to fill out and return the enclosed questionnaire.

Future developments in hardwood sawmill technology will improve the efficiency of sawmills. New technologies are being developed which will improve the quality of hardwood lumber and increase profits. Virginia Tech is examining scanning and optimizing technology in hardwood sawmills. Hardwood lumber scanning and optimizing technology refers to existing edger-optimizers, more advanced edger-optimizers, and emerging automated lumber grading systems. The information generated from this project will help sawmill managers make more informed decisions, as well as improve hardwood lumber scanning and optimizing technology. This information is critical for moving hardwood sawmill technology in the proper direction, which will ultimately increase your profits.

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Thank you very much for your time and assistance. If you have any questions or comments, please feel free to contact me at 540-231-5876 (Phone), 540-231-8868 (Fax), or sbowe@vt.edu (Email).

Sincerely,

Scott Bowe
Graduate Student

A Land-Grant University - The Commonwealth Is Our Campus

Second Cover Letter

APPENDIX B: AHP Model Questionnaire

Date: ____________ **Meeting Time: ____________**

Company Name: ____

Address: ____

Phone Number: _________________________ Fax Number: _________________________

Contact: ____

Position: ____

Current Technology: ____

1. **Do you believe that scanning and optimizing technology would benefit your sawmill?**

2. **Do you believe there is accurate and truthful information available on hardwood lumber scanning and optimizing technology?**

3. **What negative things have you heard about hardwood lumber scanning and optimizing technology?**

4. **What specific features would an edger-optimizer, trimmer-optimizer, or automated grading system need to have before you would install it in your sawmill?**

5. **When deciding to install scanning and optimizing technology, is this an individual decision (manager or owner) or group decision (management and plant staff)?**

Goal: To determine to what extent the sawmill system plays in the decision to adopt or not adopt advanced hardwood lumber scanning and optimizing technology.

AHP Model Questionnaire: Page 1

Decision Factor Comparison

Suppose you are considering installing advanced scanning and optimizing technology in your hardwood sawmill. Examples of this equipment would be advanced edger optimizers and automated grading systems. These advanced systems optimize based on more than just board size and wane information. They optimize based on NHLA grading rules using surface defect information in addition to size and wane information. You have to decide whether or not to install this technology. We have put together a short list of **decision factors** that arise when you consider installing advanced scanning and optimizing technology. Please take a few minutes to compare these **decision factors** so we can determine which ones you think are more important.

Decision Factor		Extreme							Equal							Extreme		Decision Factor
Equipment Features	9	8	7	6	5	4	3	2	**1**	2	3	4	5	6	7	8	9	Production Improvements
Equipment Features	9	8	7	6	5	4	3	2	**1**	2	3	4	5	6	7	8	9	Mill Communications
Equipment Features	9	8	7	6	5	4	3	2	**1**	2	3	4	5	6	7	8	9	Maintenance Issues
Equipment Features	9	8	7	6	5	4	3	2	**1**	2	3	4	5	6	7	8	9	Barriers
Equipment Features	9	8	7	6	5	4	3	2	**1**	2	3	4	5	6	7	8	9	Customer Requirements
Production Improvements	9	8	7	6	5	4	3	2	**1**	2	3	4	5	6	7	8	9	Mill Communications
Production Improvements	9	8	7	6	5	4	3	2	**1**	2	3	4	5	6	7	8	9	Maintenance Issues
Production Improvements	9	8	7	6	5	4	3	2	**1**	2	3	4	5	6	7	8	9	Barriers
Production Improvements	9	8	7	6	5	4	3	2	**1**	2	3	4	5	6	7	8	9	Customer Requirements
Mill Communications	9	8	7	6	5	4	3	2	**1**	2	3	4	5	6	7	8	9	Maintenance Issues
Mill Communications	9	8	7	6	5	4	3	2	**1**	2	3	4	5	6	7	8	9	Barriers
Mill Communications	9	8	7	6	5	4	3	2	**1**	2	3	4	5	6	7	8	9	Customer Requirements
Maintenance Issues	9	8	7	6	5	4	3	2	**1**	2	3	4	5	6	7	8	9	Barriers
Maintenance Issues	9	8	7	6	5	4	3	2	**1**	2	3	4	5	6	7	8	9	Customer Requirements
Barriers	9	8	7	6	5	4	3	2	**1**	2	3	4	5	6	7	8	9	Customer Requirements

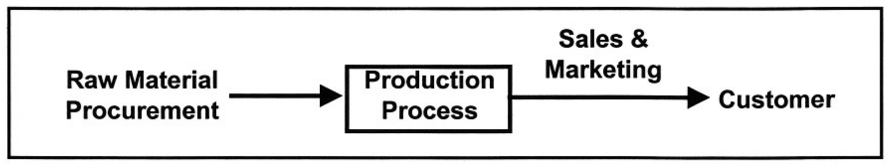
(1 = Equal, 3 = Moderate, 5 = Strong, 7 = Very Strong, 9 = Extreme)

AHP Model Questionnaire: Page 2

Extended Sawmill Comparison

Adding advanced scanning and optimizing technology to your hardwood sawmill may affect more than just the production process. To better understand your view on this, we have expanded the typical hardwood sawmill into four departments. These four departments include more than just the production process. Here the sawmill starts with *Log Procurement*. It then moves through the *Production Process* and onto *Sales & Marketing*. Finally, it finishes with the *Customer*.

When you are considering installing advanced scanning and optimizing technology, we want to understand how important you consider these four departments to be. Below we have listed a **decision factor** that arises when you consider installing new sawmill equipment. If you only considered this decision factor, which department is more important when you consider buying advanced scanning and optimizing technology?



Equipment Features

Sawmill Department	Extreme								Equal								Extreme	Sawmill Department
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Production Process
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Sales & Marketing
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer
Production Process	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Sales & Marketing
Production Process	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer
Sales & Marketing	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer

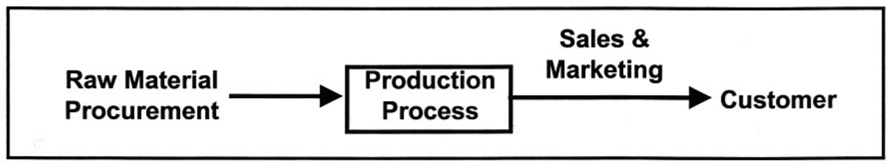
(1 = Equal, 3 = Moderate, 5 = Strong, 7 = Very Strong, 9 = Extreme)

AHP Model Questionnaire: Page 3

Extended Sawmill Comparison

Adding advanced scanning and optimizing technology to your hardwood sawmill may affect more than just the production process. To better understand your view on this, we have expanded the typical hardwood sawmill into four departments. These four departments include more than just the production process. Here the sawmill starts with *Log Procurement*. It then moves through the *Production Process* and onto *Sales & Marketing*. Finally, it finishes with the *Customer*.

When you are considering installing advanced scanning and optimizing technology, we want to understand how important you consider these four departments to be. Below we have listed a **decision factor** that arises when you consider installing new sawmill equipment. If you only considered this decision factor, which department is more important when you consider buying advanced scanning and optimizing technology?



Production Improvements

Sawmill Department	Extreme								Equal								Extreme	Sawmill Department
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Production Process
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Sales & Marketing
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer
Production Process	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Sales & Marketing
Production Process	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer
Sales & Marketing	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer

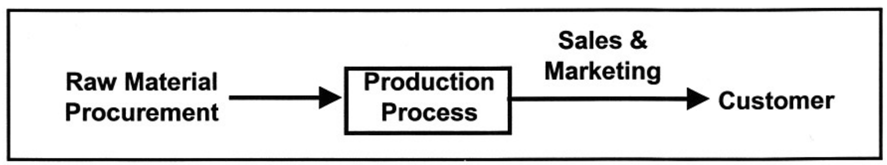
(1 = Equal, 3 = Moderate, 5 = Strong, 7 = Very Strong, 9 = Extreme)

AHP Model Questionnaire: Page 4

Extended Sawmill Comparison

Adding advanced scanning and optimizing technology to your hardwood sawmill may affect more than just the production process. To better understand your view on this, we have expanded the typical hardwood sawmill into four departments. These four departments include more than just the production process. Here the sawmill starts with *Log Procurement*. It then moves through the *Production Process* and onto *Sales & Marketing*. Finally, it finishes with the *Customer*.

When you are considering installing advanced scanning and optimizing technology, we want to understand how important you consider these four departments to be. Below we have listed a **decision factor** that arises when you consider installing new sawmill equipment. If you only considered this decision factor, which department is more important when you consider buying advanced scanning and optimizing technology?



Mill Communications

Sawmill Department	Extreme								Equal								Extreme	Sawmill Department
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Production Process
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Sales & Marketing
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer
Production Process	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Sales & Marketing
Production Process	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer
Sales & Marketing	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer

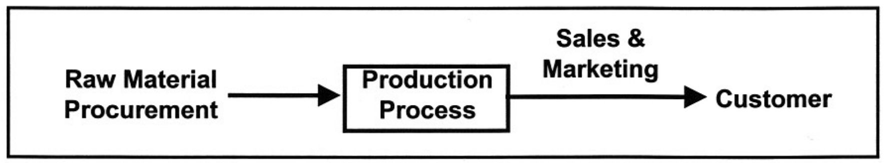
(1 = Equal, 3 = Moderate, 5 = Strong, 7 = Very Strong, 9 = Extreme)

AHP Model Questionnaire: Page 5

Extended Sawmill Comparison

Adding advanced scanning and optimizing technology to your hardwood sawmill may affect more than just the production process. To better understand your view on this, we have expanded the typical hardwood sawmill into four departments. These four departments include more than just the production process. Here the sawmill starts with *Log Procurement*. It then moves through the *Production Process* and onto *Sales & Marketing*. Finally, it finishes with the *Customer*.

When you are considering installing advanced scanning and optimizing technology, we want to understand how important you consider these four departments to be. Below we have listed a **decision factor** that arises when you consider installing new sawmill equipment. If you only considered this decision factor, which department is more important when you consider buying advanced scanning and optimizing technology?



Maintenance Issues

Sawmill Department	Extreme								Equal								Extreme	Sawmill Department
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Production Process
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Sales & Marketing
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer
Production Process	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Sales & Marketing
Production Process	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer
Sales & Marketing	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer

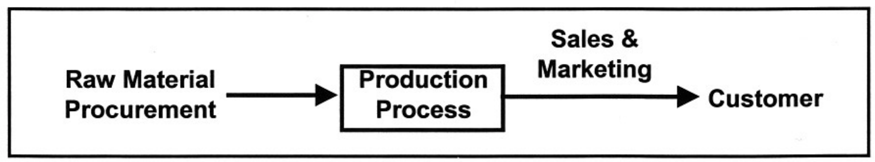
(1 = Equal, 3 = Moderate, 5 = Strong, 7 = Very Strong, 9 = Extreme)

AHP Model Questionnaire: Page 6

Extended Sawmill Comparison

Adding advanced scanning and optimizing technology to your hardwood sawmill may affect more than just the production process. To better understand your view on this, we have expanded the typical hardwood sawmill into four departments. These four departments include more than just the production process. Here the sawmill starts with *Log Procurement*. It then moves through the *Production Process* and onto *Sales & Marketing*. Finally, it finishes with the *Customer*.

When you are considering installing advanced scanning and optimizing technology, we want to understand how important you consider these four departments to be. Below we have listed a **decision factor** that arises when you consider installing new sawmill equipment. If you only considered this decision factor, which department is more important when you consider buying advanced scanning and optimizing technology?



Barriers

Sawmill Department	Extreme								Equal								Extreme	Sawmill Department
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Production Process
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Sales & Marketing
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer
Production Process	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Sales & Marketing
Production Process	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer
Sales & Marketing	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer

(1 = Equal, 3 = Moderate, 5 = Strong, 7 = Very Strong, 9 = Extreme)

AHP Model Questionnaire: Page 7

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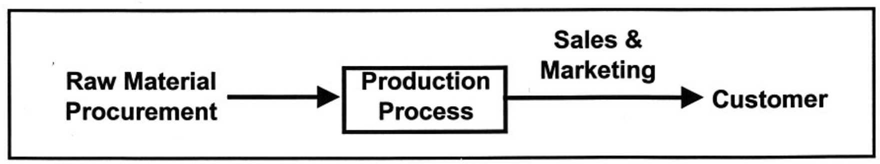

Customer Requirements

Sawmill Department	Extreme								Equal								Extreme	Sawmill Department
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Production Process
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Sales & Marketing
Log Procurement	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer
Production Process	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Sales & Marketing
Production Process	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Customer
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AHP Model Questionnaire: Page 8

Decision Factors

Equipment Features
Availability of Vendor Support
Training from Vendor
Ability to Upgrade
System Lifespan
Ease of Use

Production Improvements
Improved Raw Material Recovery
Improved Lumber Consistency
Improved Lumber Quality
Increased Lumber Revenues
Increased Production Levels

Mill Communications
Advice from Production Supervisors
Advice from Sales Department
Advice from Customers

Maintenance Issues
Training of New Operators
Installation Downtime
Operational Costs
Maintenance Costs

Barriers
Existing Mill Layout Restrictions
Initial Cost
New Mill Installation

Customer Requirements
Size Requirements
Grade Requirements
Sorting Requirements

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VITA

Scott Arthur Bowe

Scott Arthur Bowe was born in Chippewa Falls, Wisconsin on December 6th, 1969. He earned his B.S. in Forest Science from the University of Wisconsin-Madison in 1992 and earned his M.S. in Wood Products Extension from the University of Minnesota in 1997. Before returning to school for his masters, Scott worked as an Extension Specialist for the Department of Forestry at the University of Wisconsin-Madison. Scott continued his graduate work in wood products at Virginia Tech when after receiving the USDA National Needs Fellowship and the Virginia Tech Graduate School Cunningham Doctoral Fellowship. Scott's interest in forest products stems from over ten years experience in the residential and commercial construction industry.